Role of synaptic and representational dynamics in learning and memory

CALIBRE Symposium

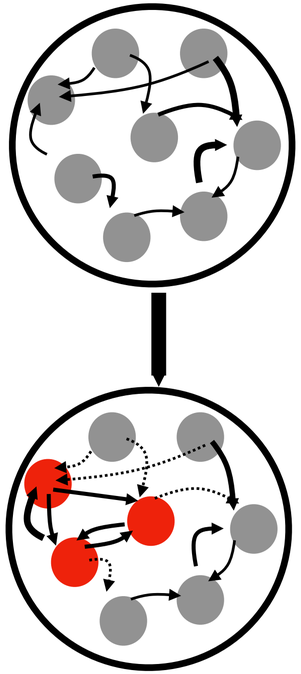
Maanasa Natrajan

October 27th, 2026

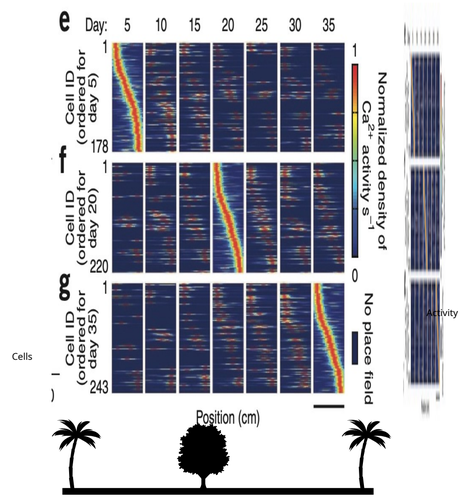
Learn

Maintain memories

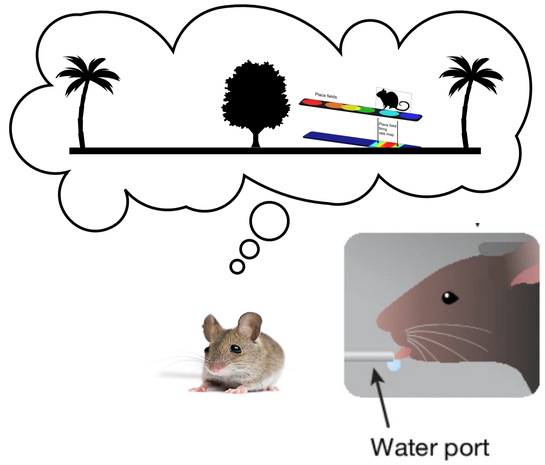
Synapse



Representation



Cognition & Behavior



Role of synaptic and representational dynamics in learning and memory.

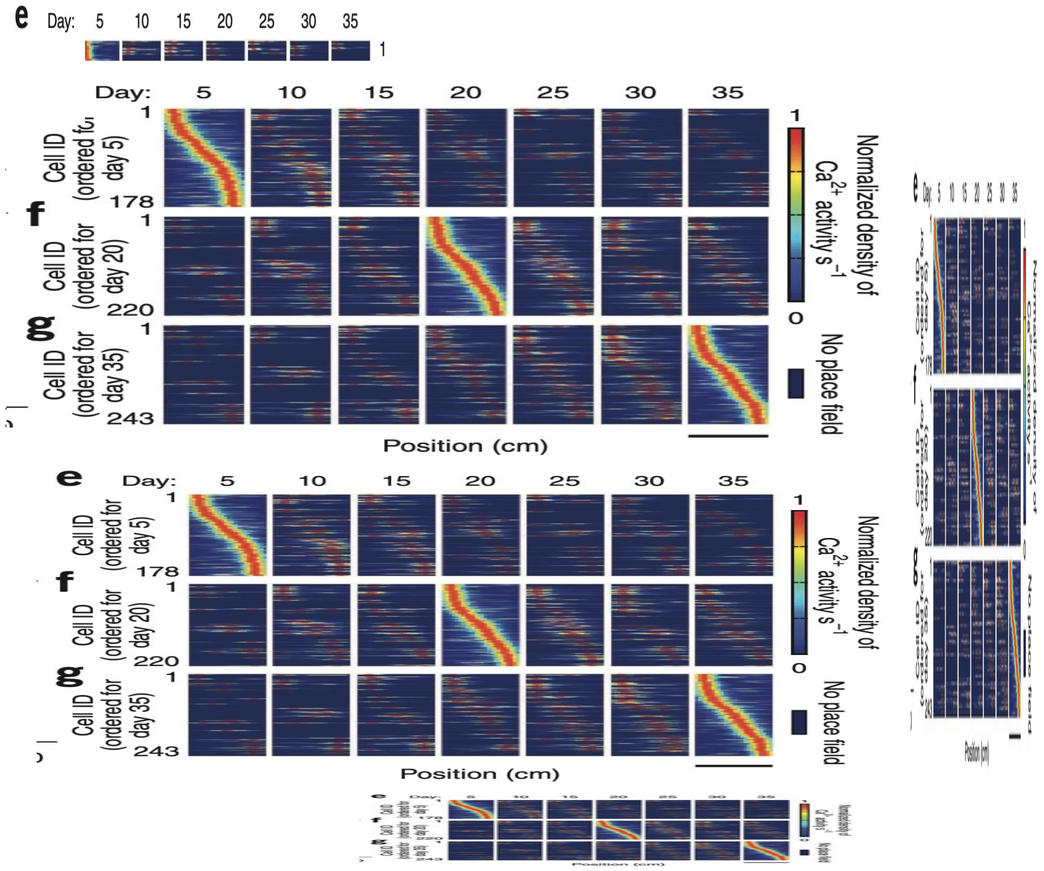
Part 1: Investigate whether drift as random exploration of solution space can help robust **maintenance** of memories.

Part 2: Characterize representational changes during cognitive map **learning**, and model these learning dynamics.

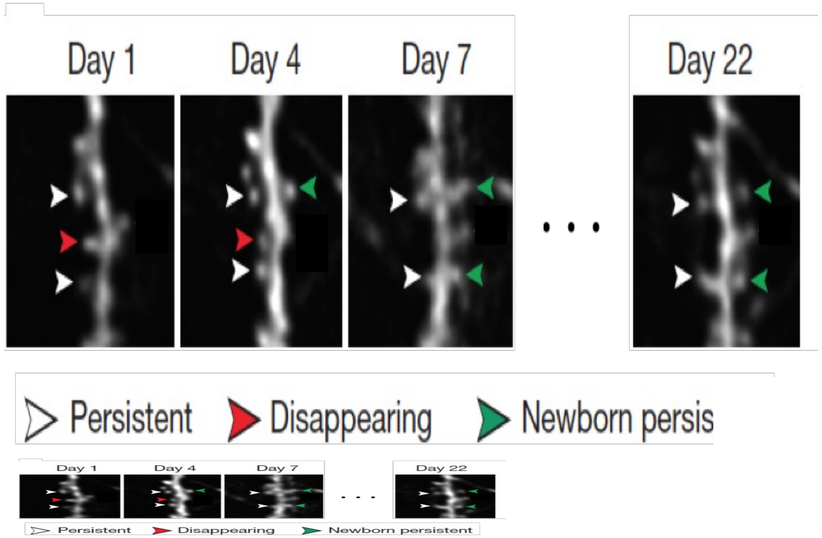
Memory maintenance

Learning

Synapses and representations change while memories and behavior seem to be maintained

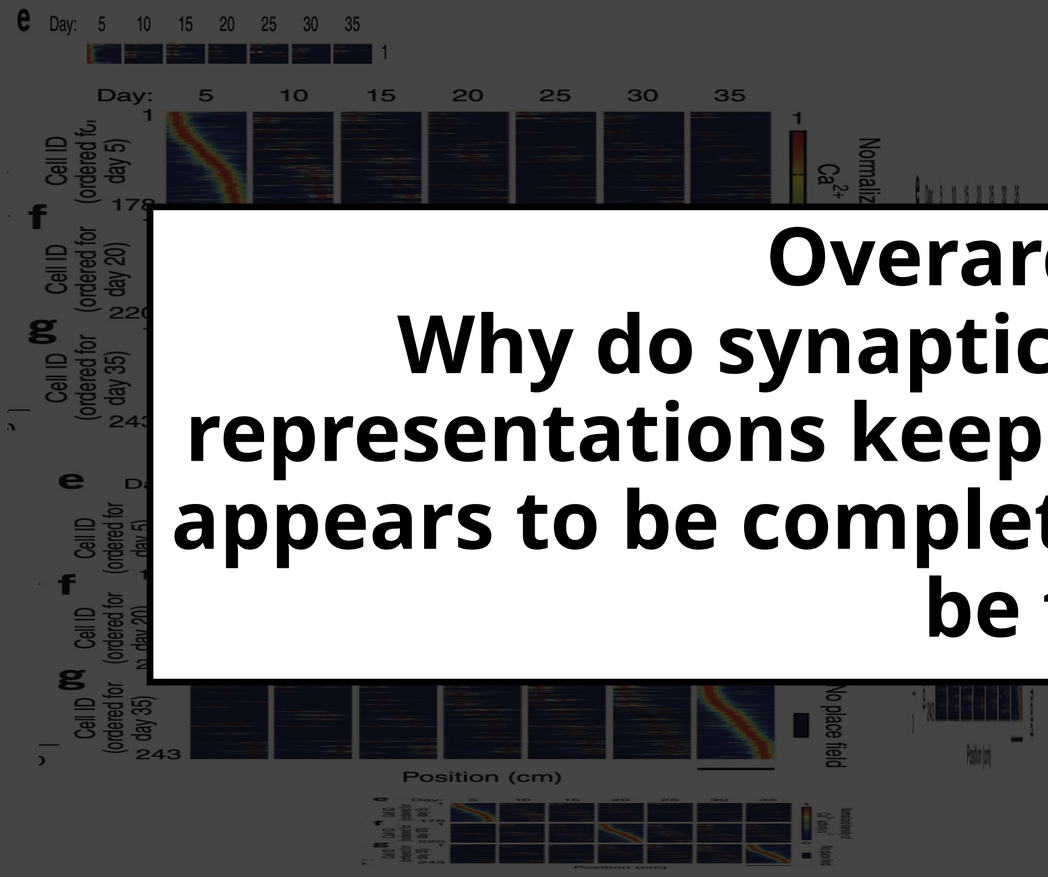


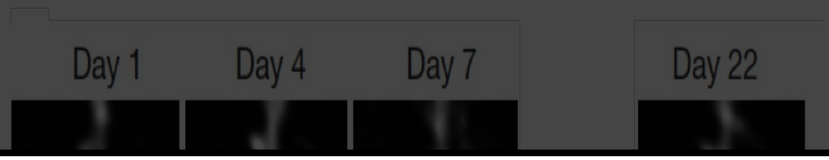
.Ziv*, Burns* et al., *Nat. Neurosci*., 2013



Attardo*, Fitzgerald*, Schnitzer, *Nature,* 2015.

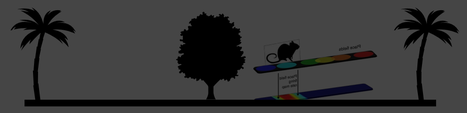
Synapses and representations change while memories and behavior seem to be maintained





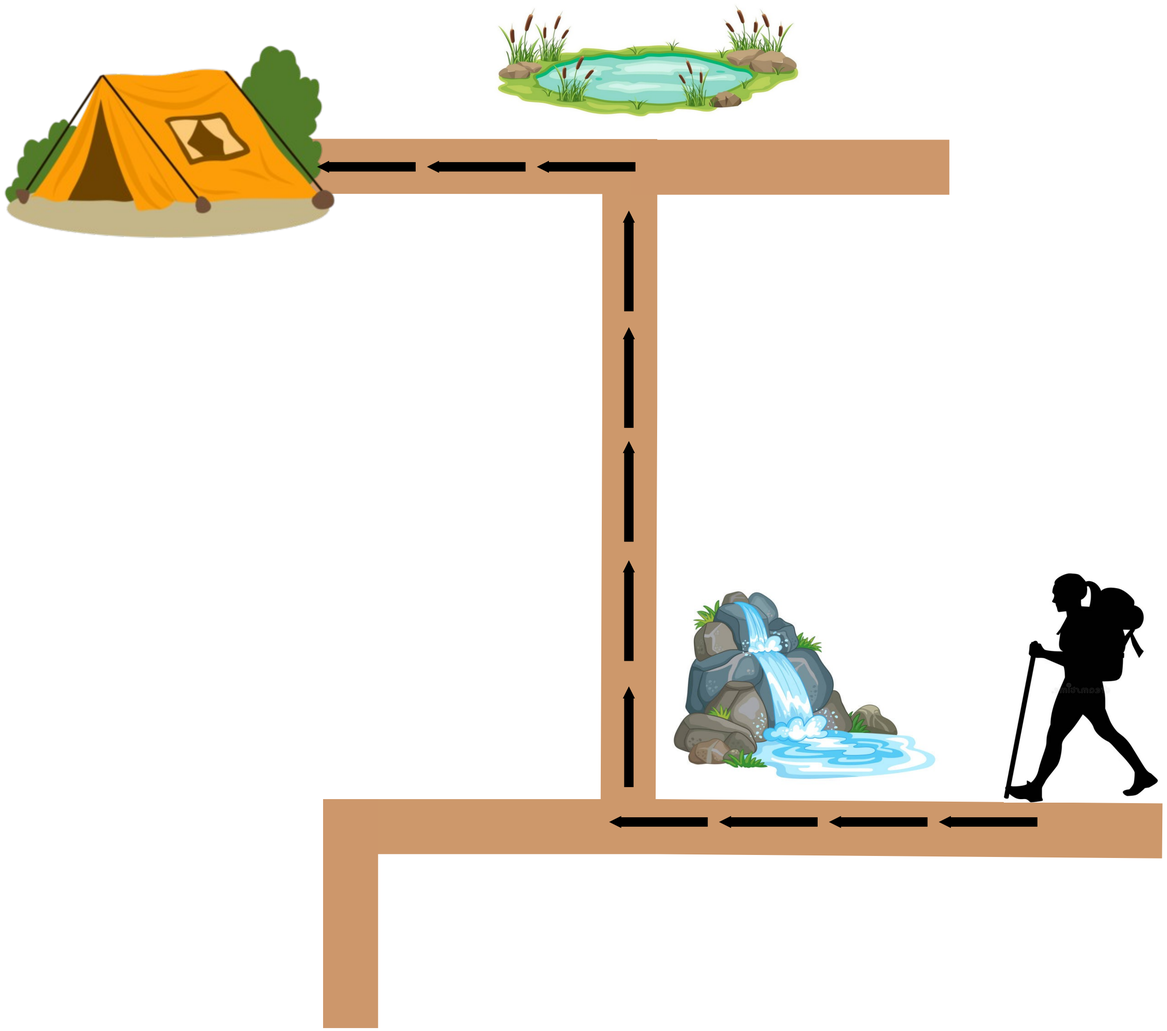
Overarching Question

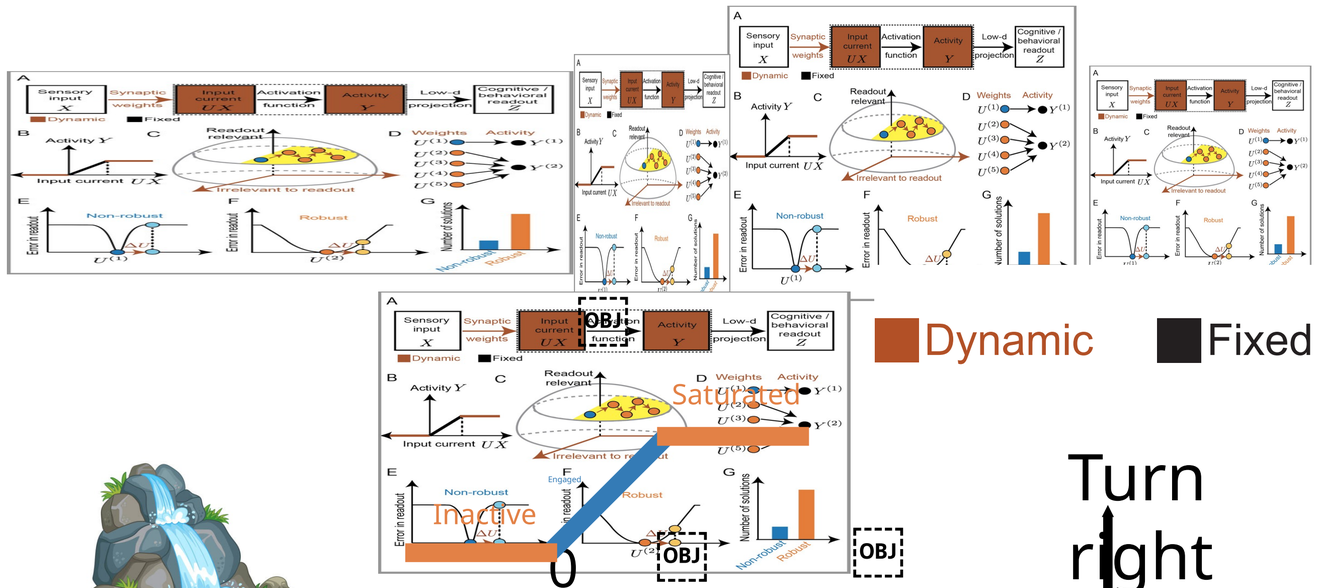
Why do synaptic connections and neural representations keep changing even after learning appears to be complete? Could this ongoing change be functional?



.Ziv*, Burns* et al., 2013

Modeling framework





Dynamic

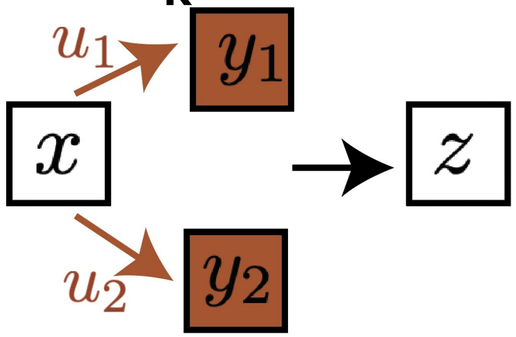
Fixed

Turn right

Turn left

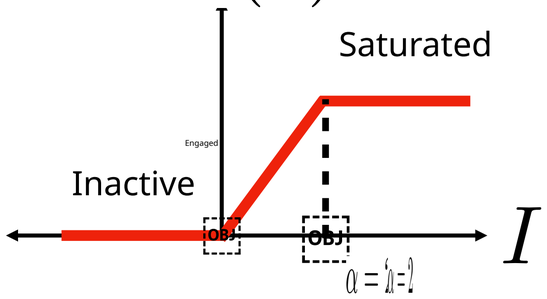
Toy example : Drift as diffusion in the solution space

Network



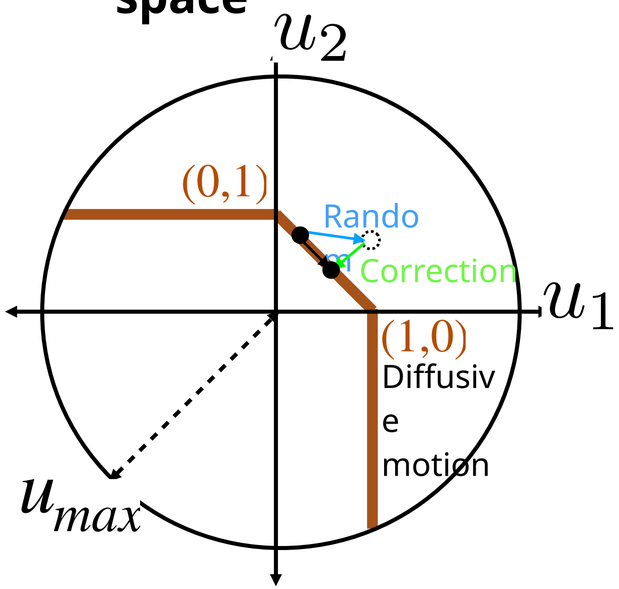
$$y_i = \Phi(u_i x)$$

Nonlinearity $\Phi(I)$



$$z = y_1 + y_2$$

Solution space



Task: Store

$$(x, z) = (1, 1)$$

Requirement

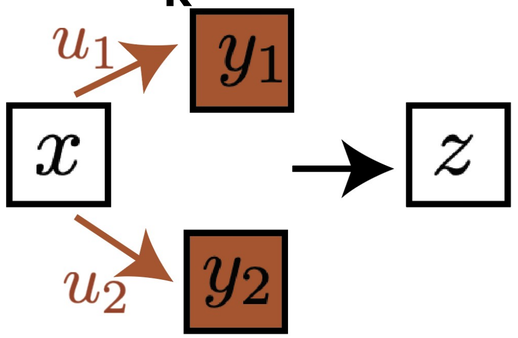
$$y_1 + y_2 = 1$$

$$\Phi(u_1) + \Phi(u_2) = 1$$

1. Do representations uncovered by drift differ from those initially learned?
2. Could drift-induced representations offer any advantages that initially learned solutions lack?

Toy example : Drift as diffusion in the solution space

Network



$$y_i = \Phi(u_i x)$$
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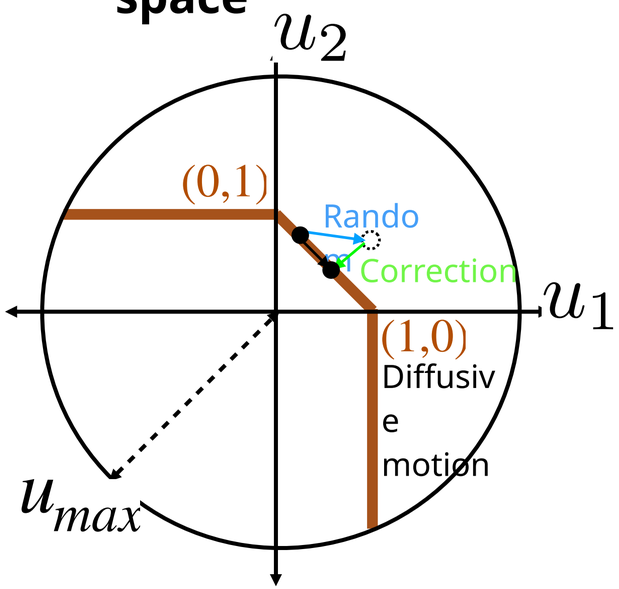
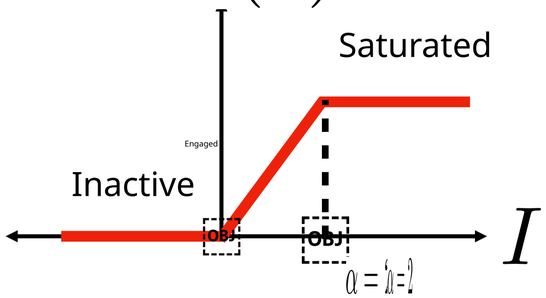
Solution space



Nonlinearity $\Phi(I)$



Task:

$$(x, z) = (1, 1)$$

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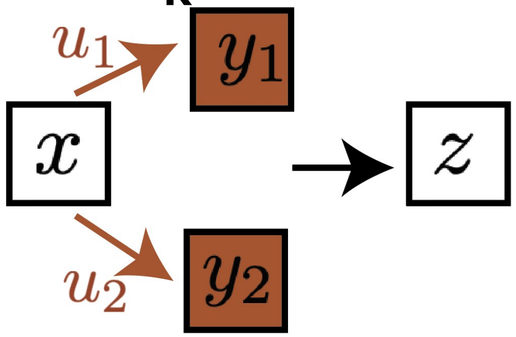
Toy example : Drift can lead to sparsely engaged solutions

Network



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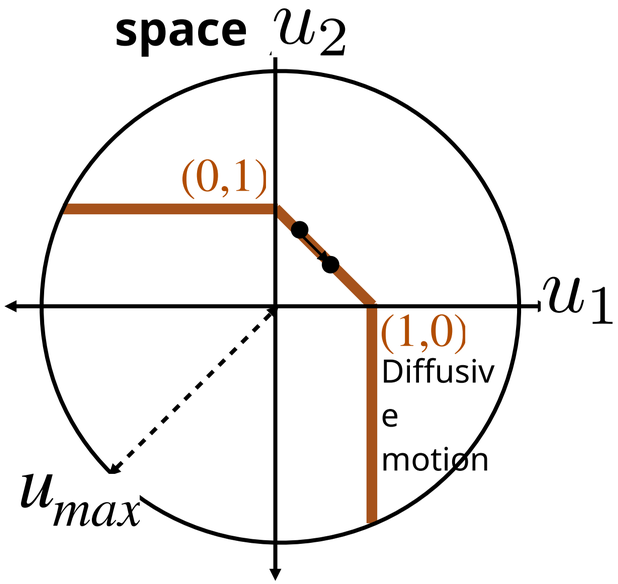
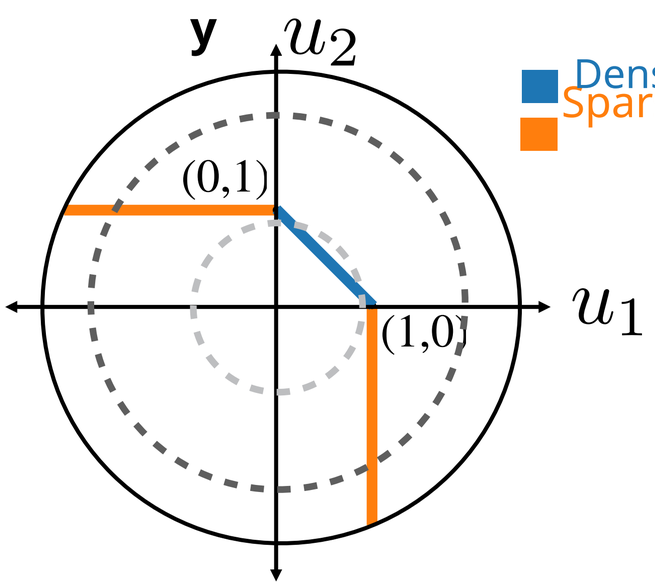
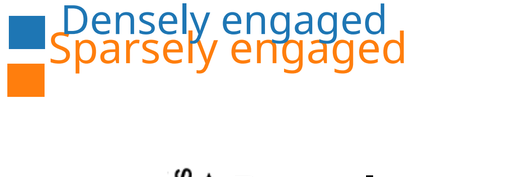
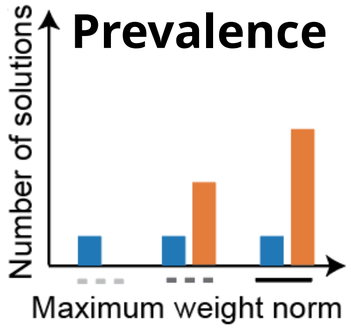


Sparsity







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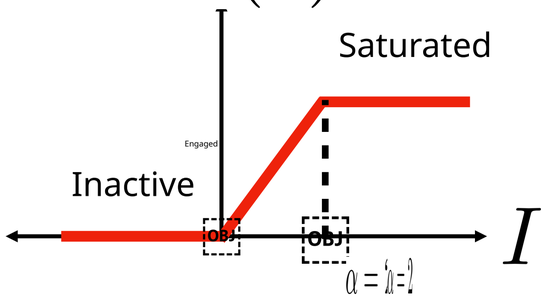

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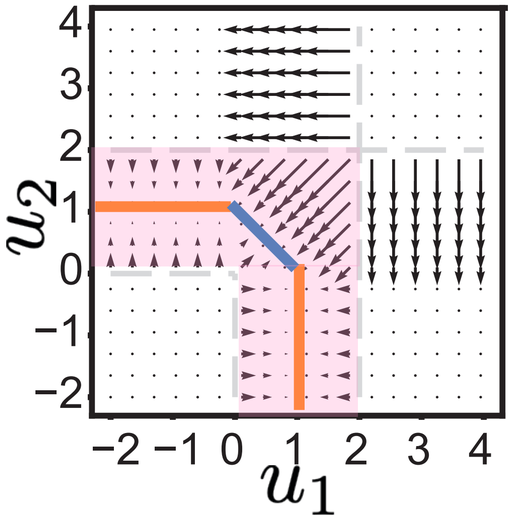
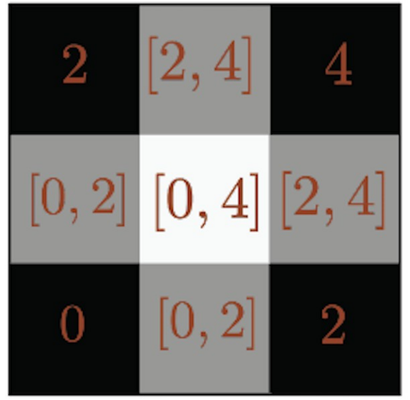
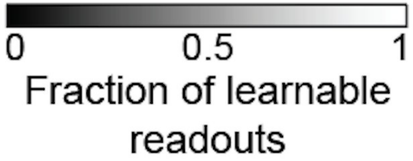
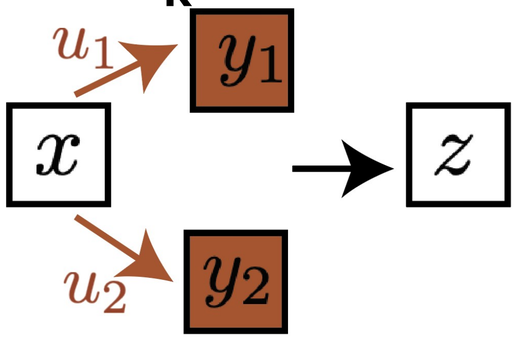






Toy example : Drift can lead to sparsely engaged, robust solutions

Network



$$y_i = \Phi(u_i x)$$
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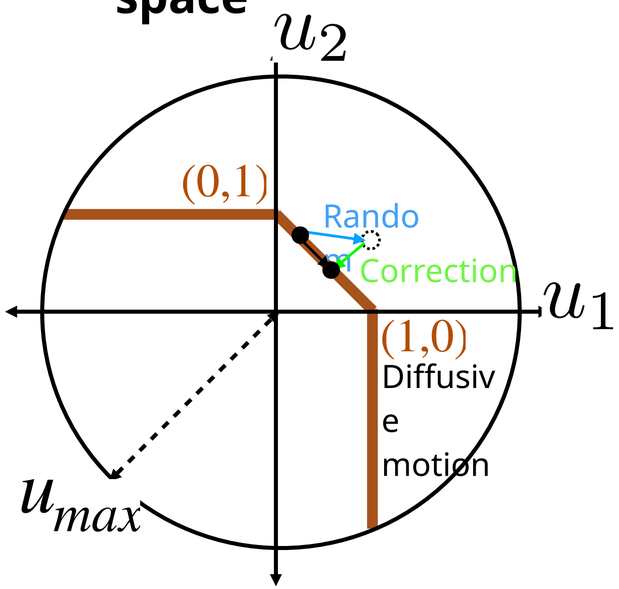
Solution space



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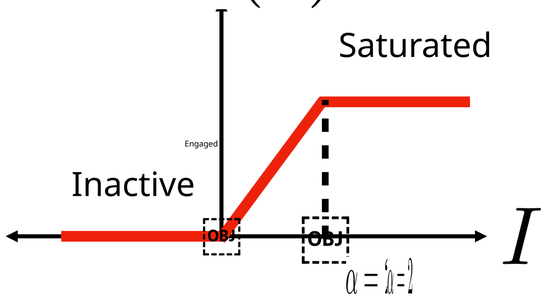

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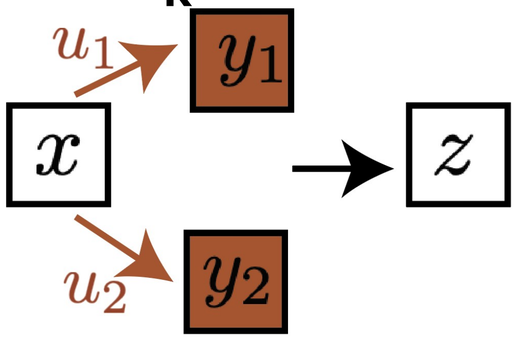

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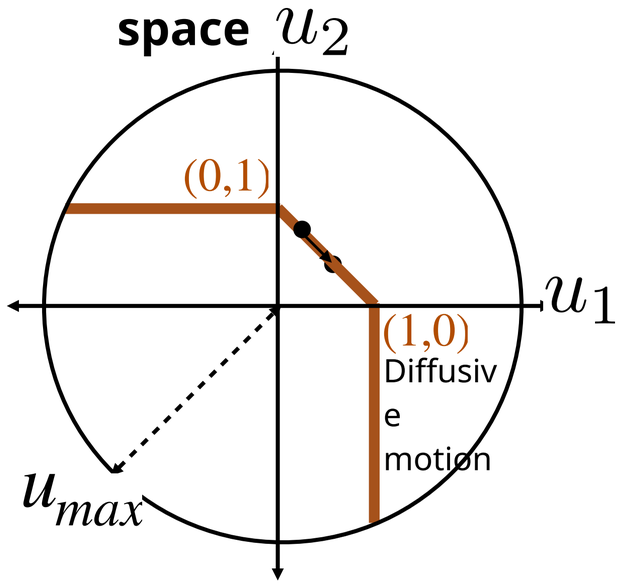
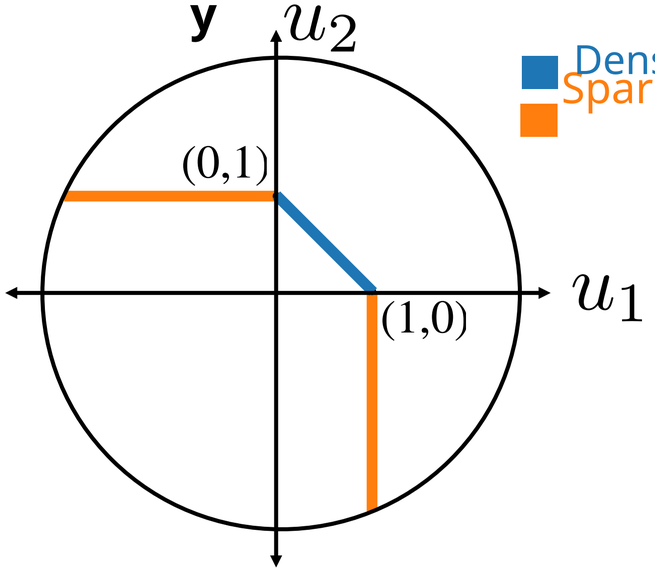
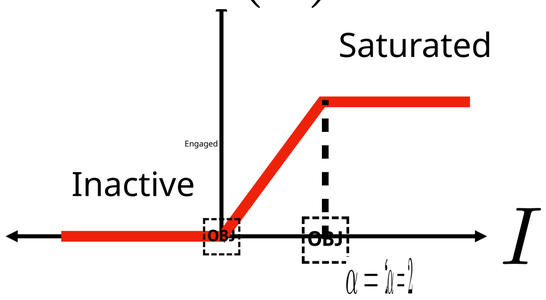


Sparsity



Densely engaged
Sparsely engaged

Nonlinearity $\Phi(I)$



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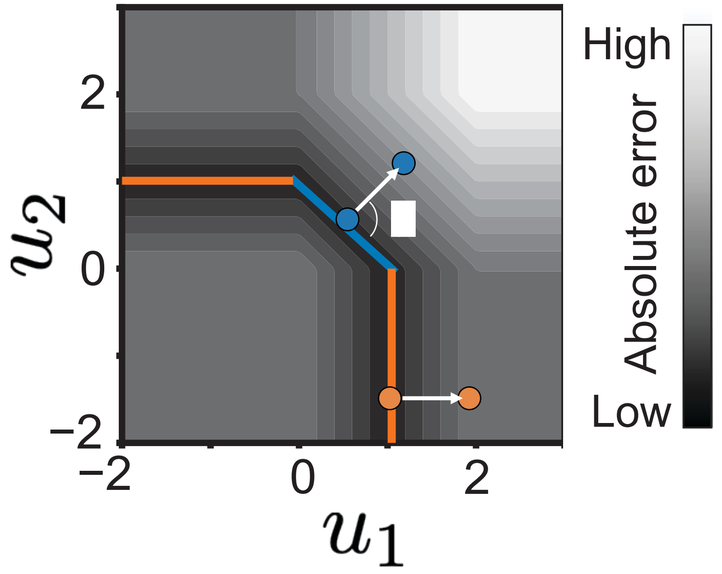
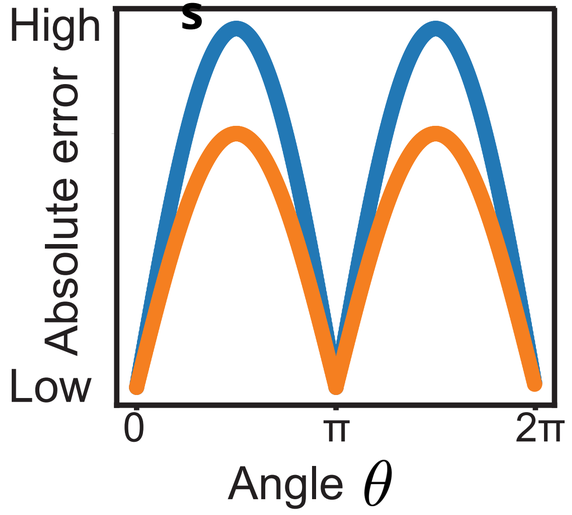
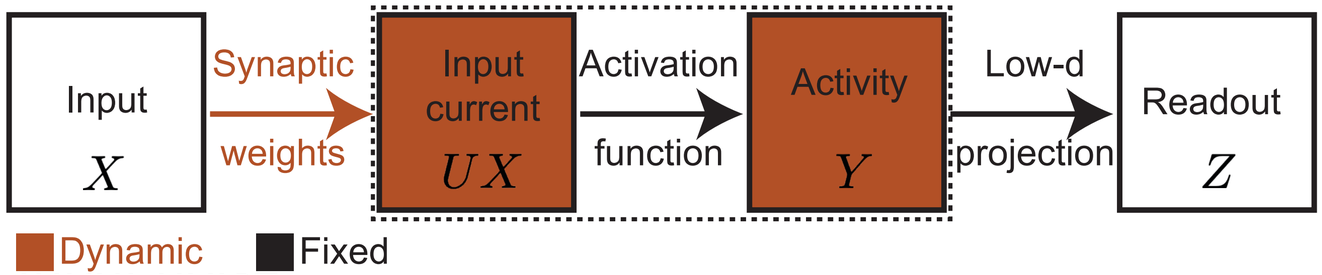
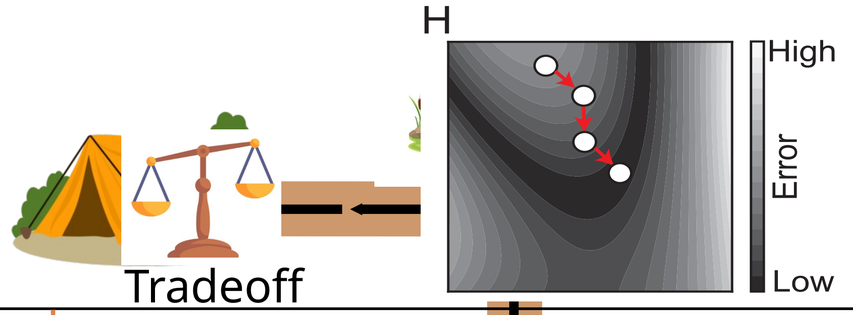


Robustness



Drift improves robustness at the cost of learnability

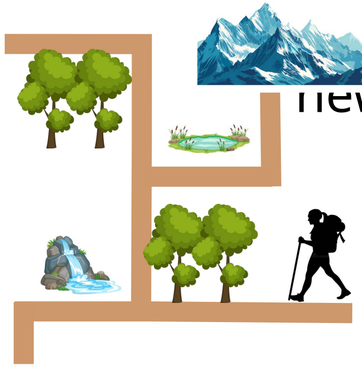






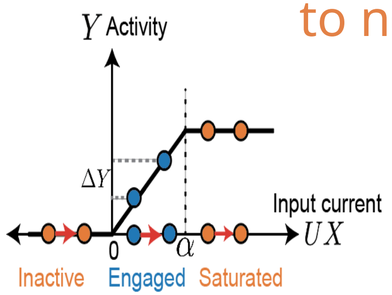
Weight perturbation

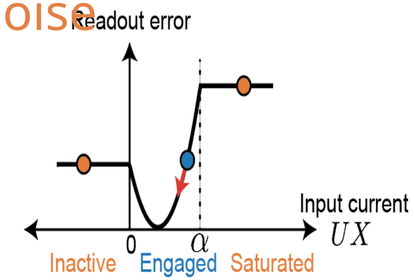
Change in input current



loring new trails

Disengaged neurons lack gradients improving robustness to noise





Robust regime
Sparsely engaged

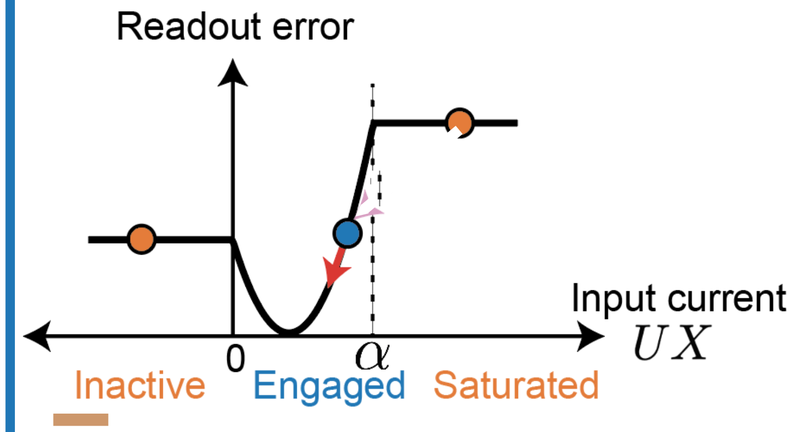
Drift

Allocation

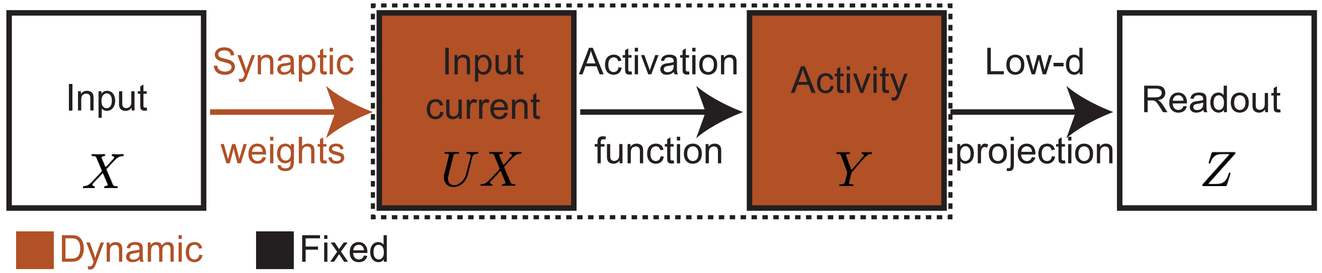
Learnable regime
Densely engaged

Robust regime
Sparsely engaged

Engaged neurons provide gradients enabling learning

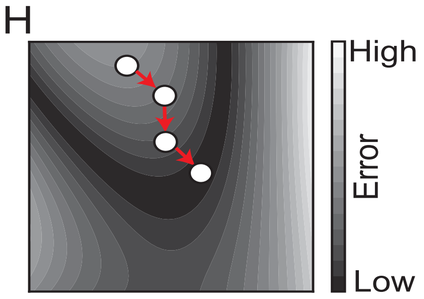


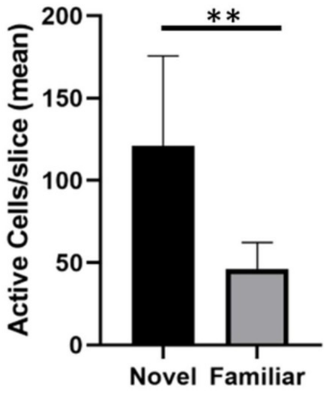
Drift with allocation help dynamically overcome learnability-robustness tradeoff





Tradeoff





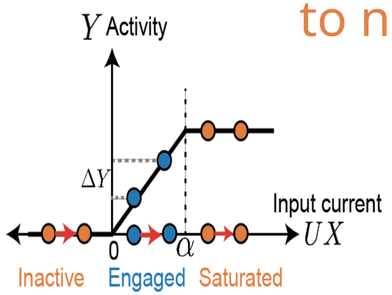
Mazurkiewicz et al., *Brain .Research*, 2022

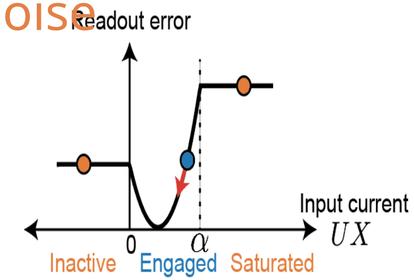
Allocation

Novel stimulus or environment

Make more neurons Engaged for the new stimulus

Disengaged neurons lack gradients improving robustness to noise





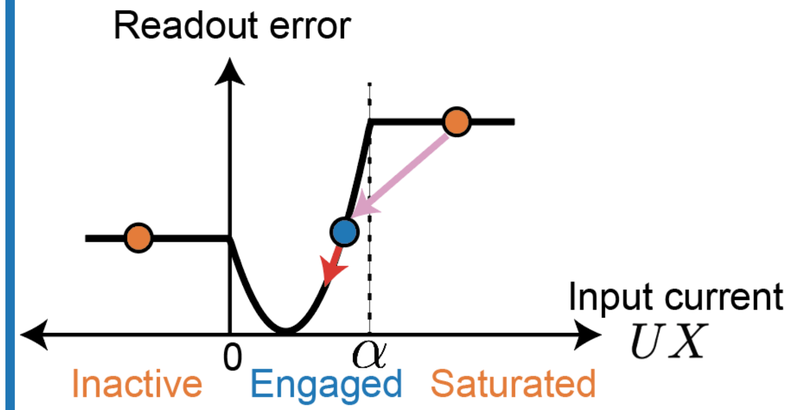
Robust regime Sparsely engaged

Drift

Allocation

Learnable regime Densely engaged

Engaged neurons provide gradients enabling learning



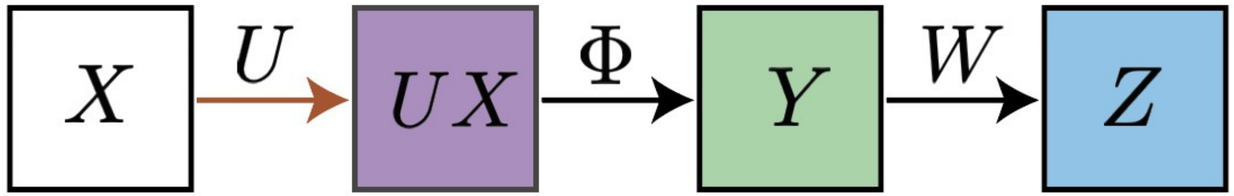
Robust regime Sparsely engaged

Drift

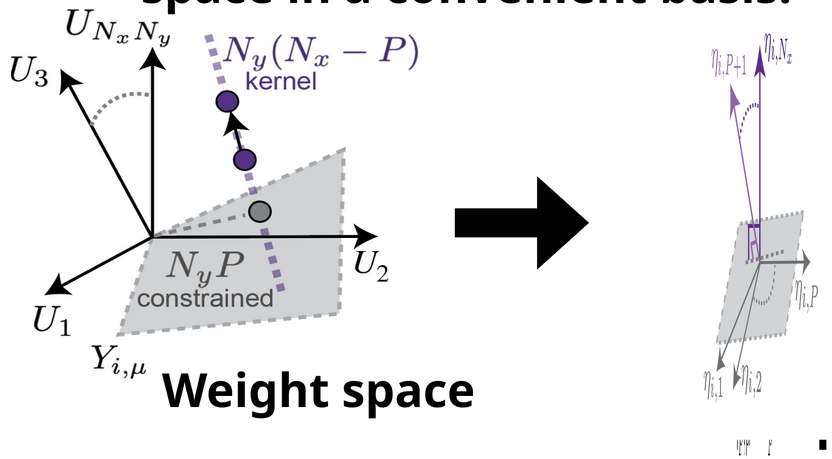
Learnable regime Densely engaged

Solution space framework

Task: Store P input-output mappings

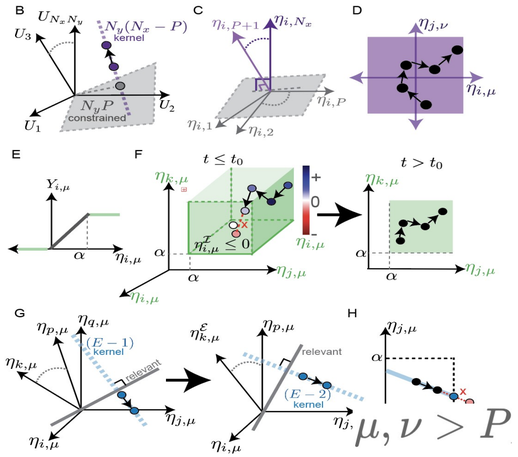


Step 1: Locally characterize the solution space in a convenient basis.

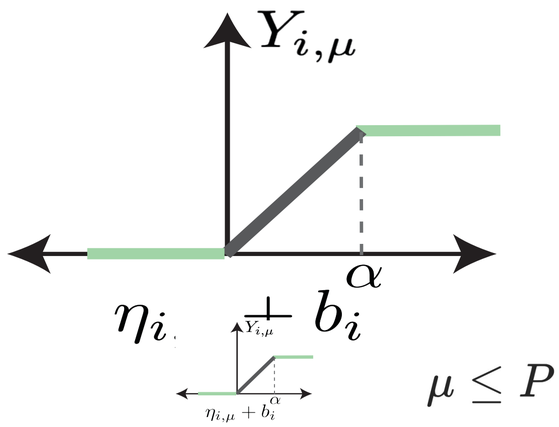


Weight space

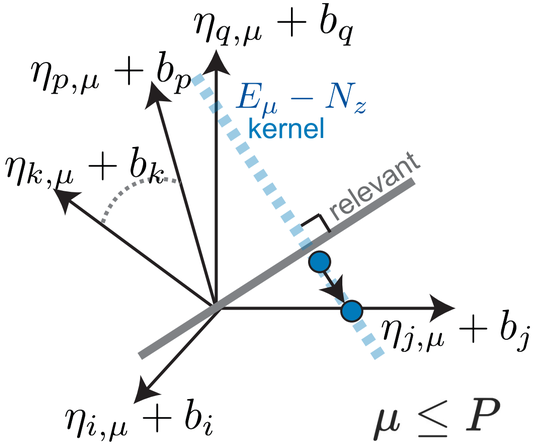
Unconstrained



Inactive and Saturated

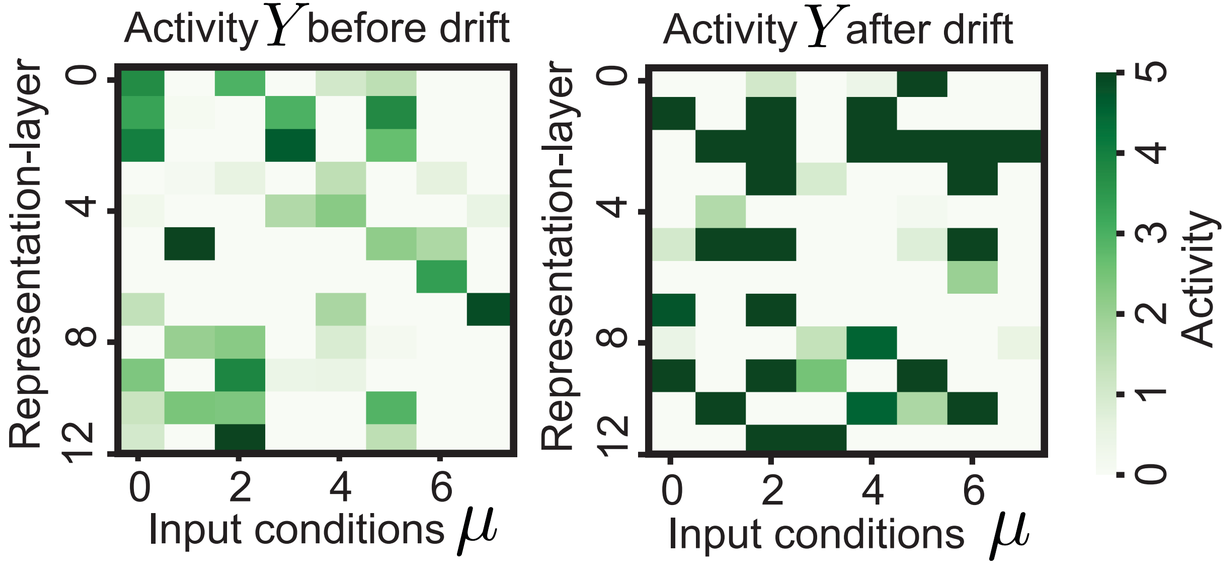


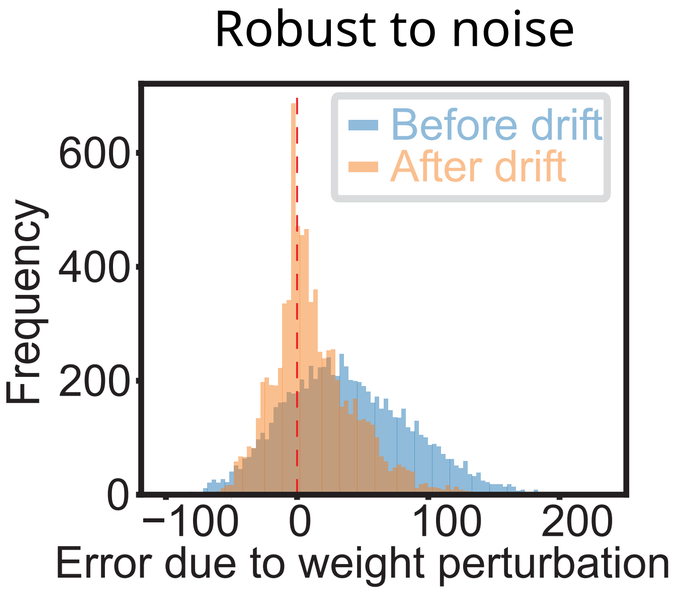
Engaged

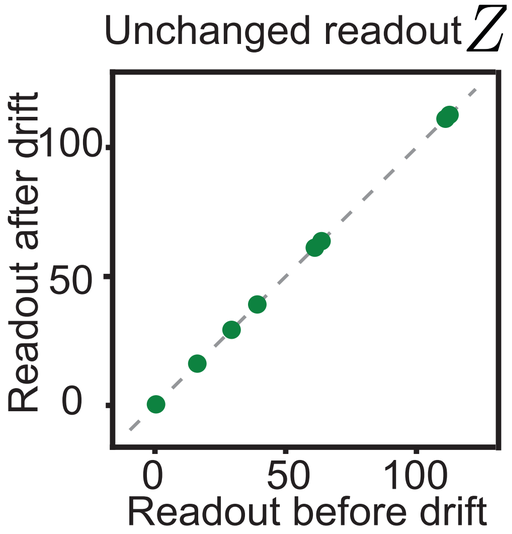


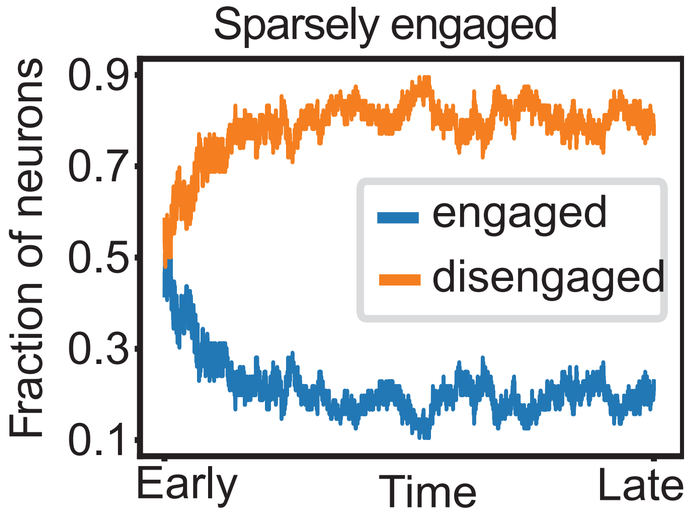
Step 2: Use these coordinates to simulate drift.

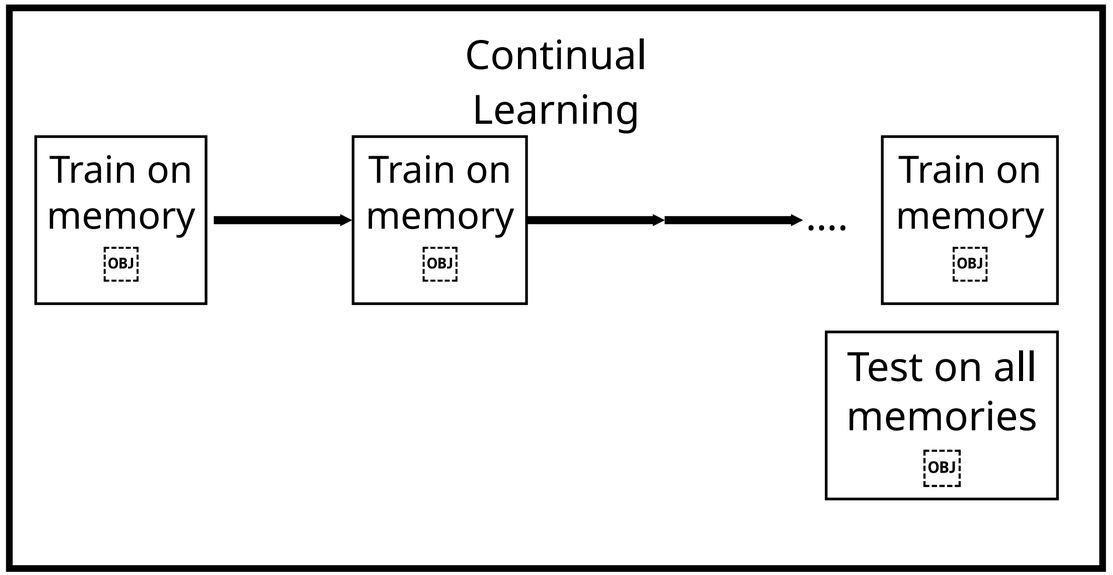
Drift finds sparsely engaged solutions robust to noise and continual learning



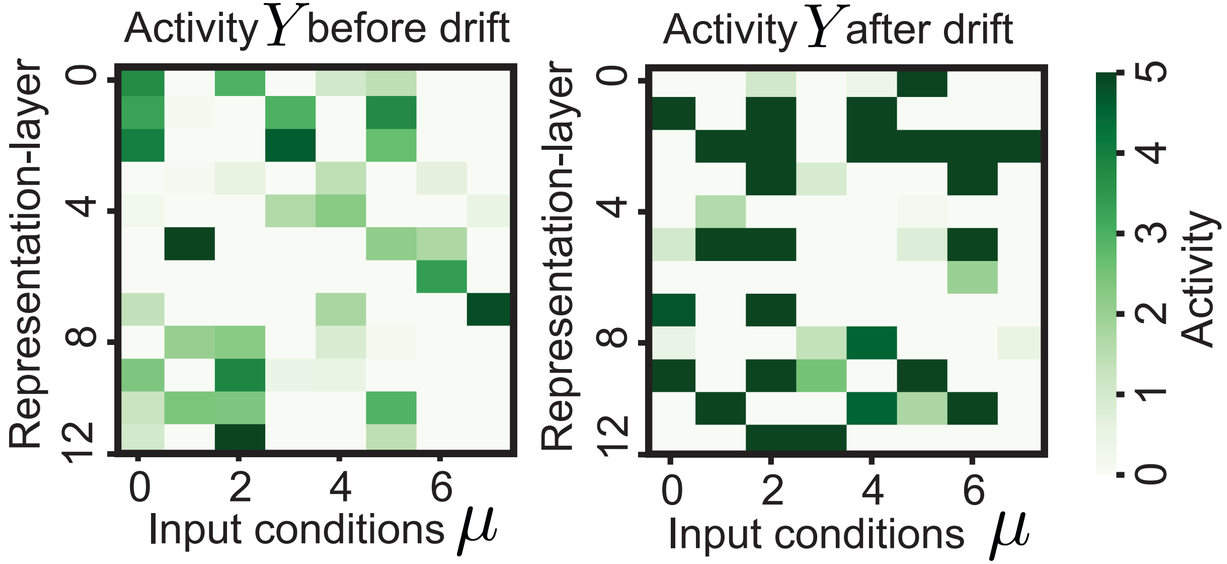


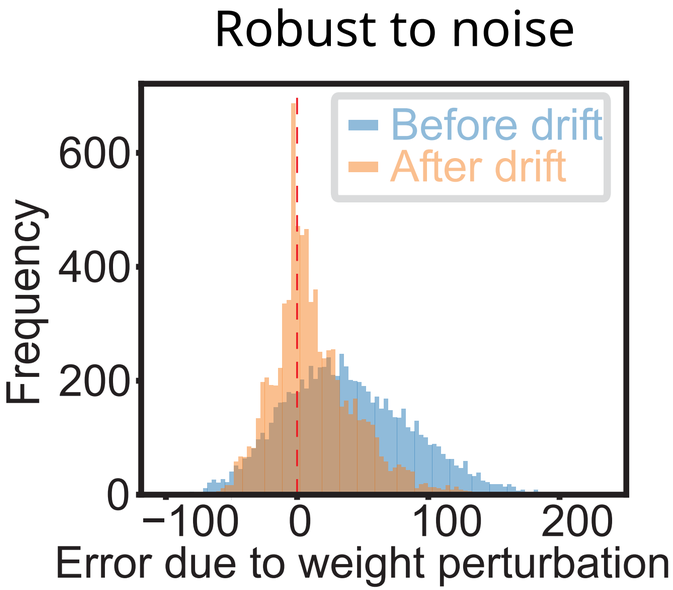


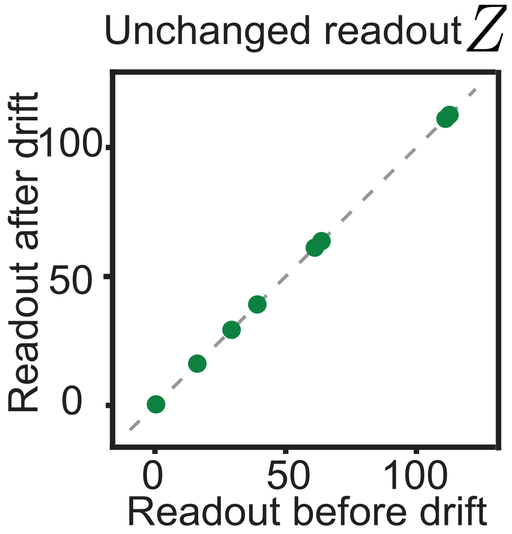


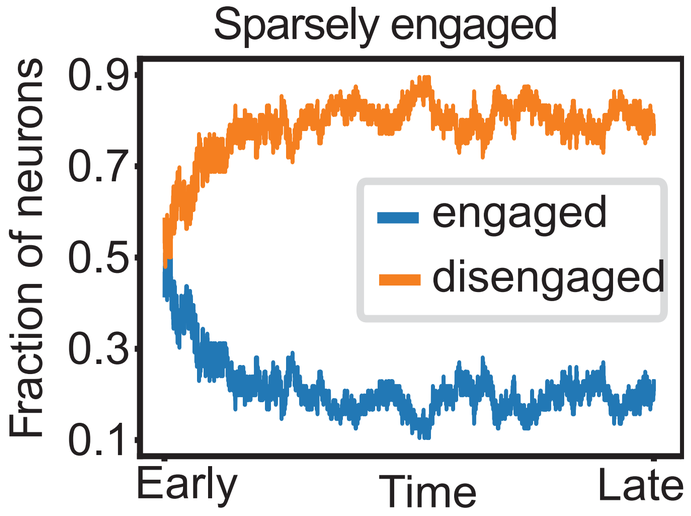


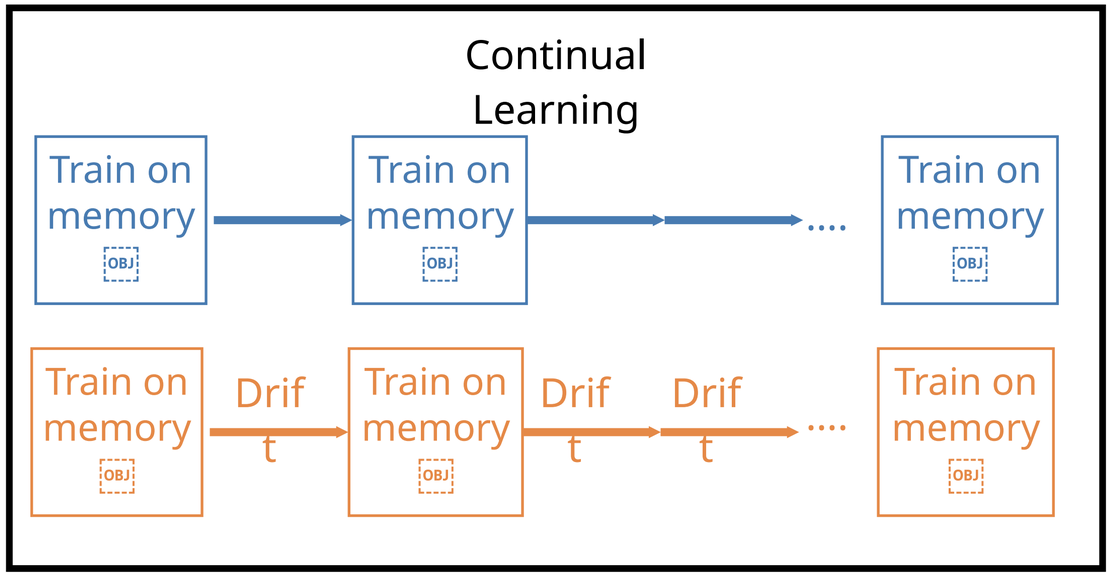
Drift finds sparsely engaged solutions robust to noise and continual learning



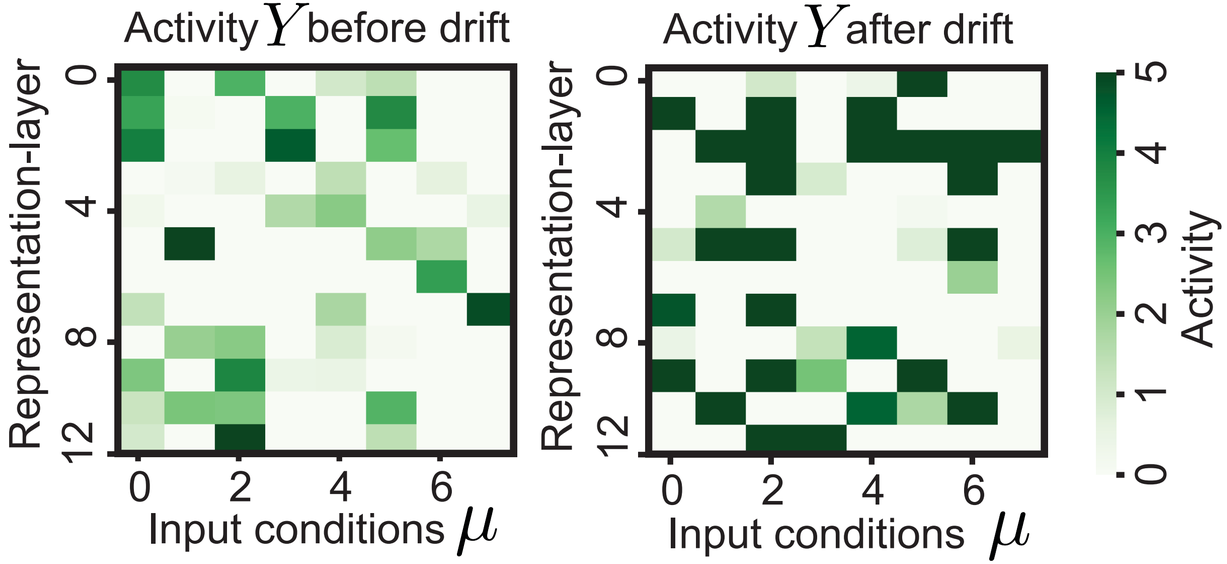


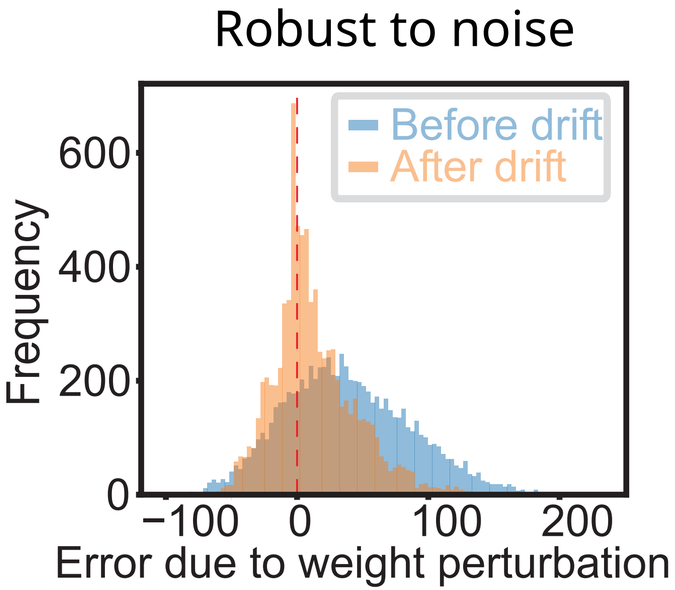


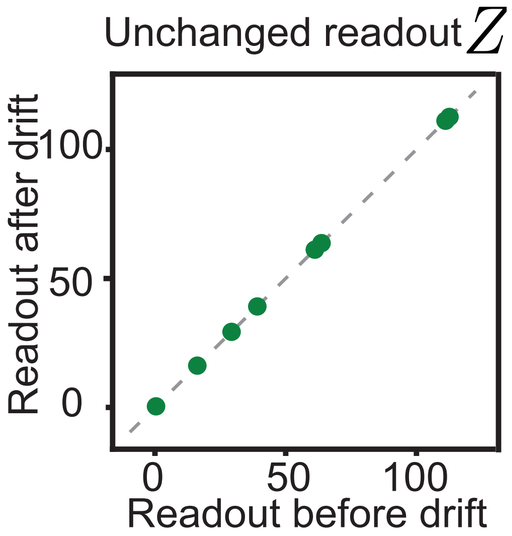


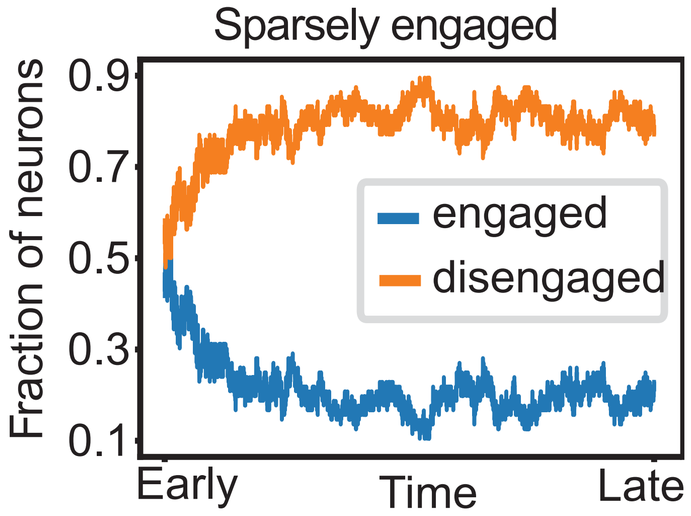


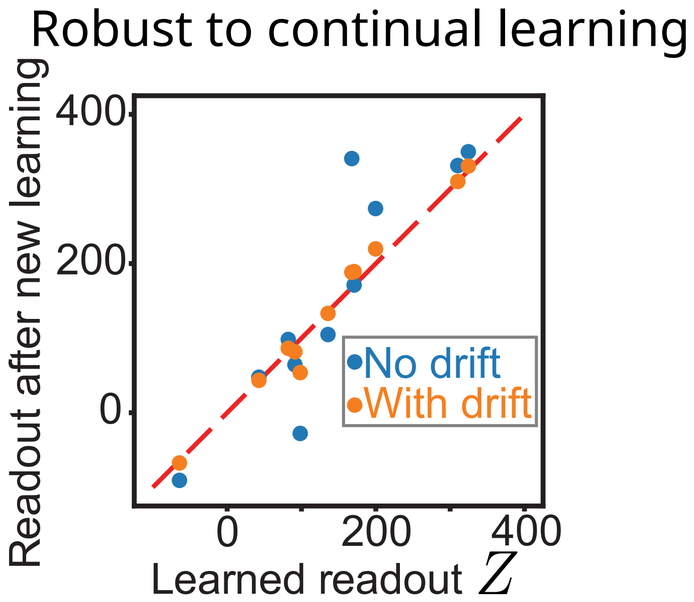
Drift finds sparsely engaged solutions robust to noise and continual learning









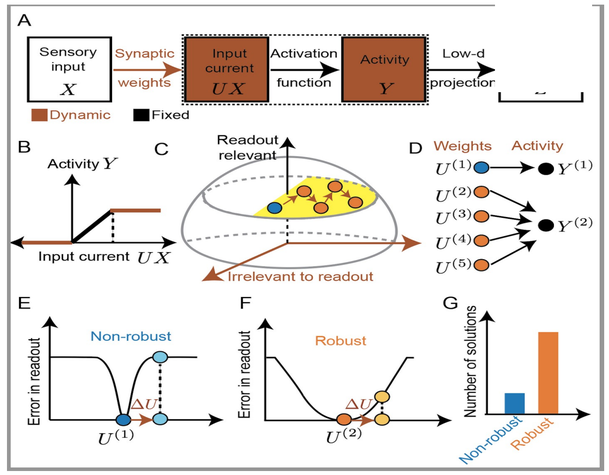


1. **Do representations uncovered by drift differ from those initially learned?**

   Yes, drift finds sparse representations while initially learned solutions are likely to be dense.

2. **Could drift-induced representations offer any advantages that initially learned solutions lack?**

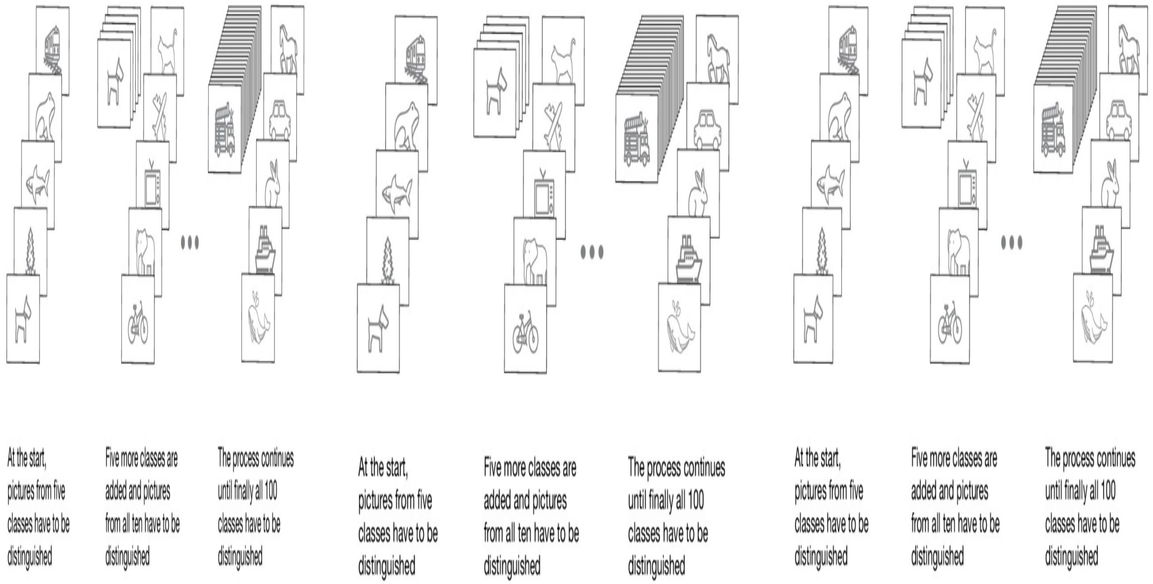
   Drift-induced representations are more robust to noise and continual learning.





Natrajan, M., & Fitzgerald, J. E. Stability through plasticity: Finding robust memories through representational drift. *Proceedings of the National Academy of Sciences* (2025).

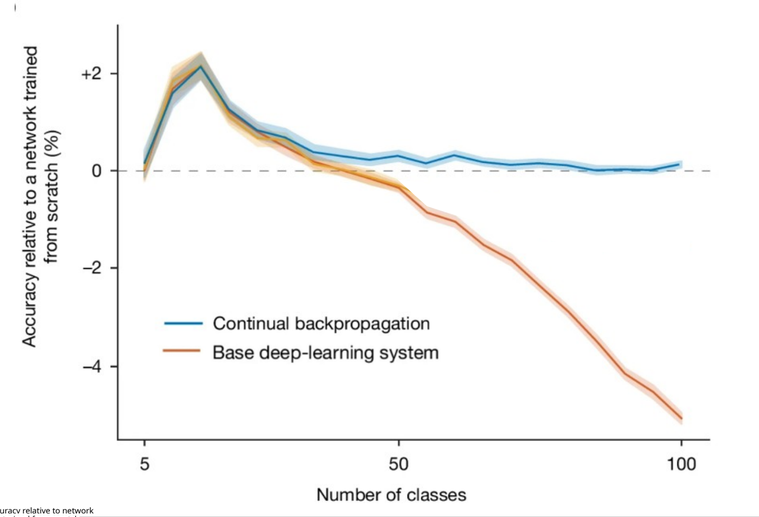
Relevance to AI: Allocation-like procedure rescues plasticity



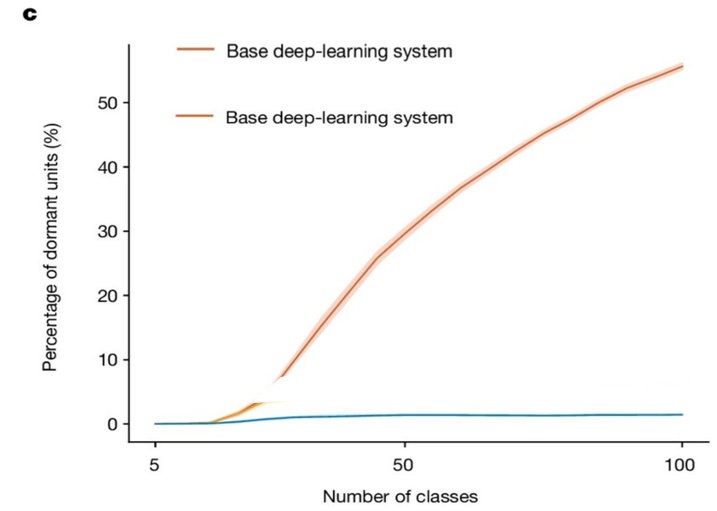
Allocation-like procedure

Choose neurons with low utility for previous tasks → Re-initialize input weights to make them active. Set output weights to zero

.Dohare et al., *Nature*., 2024



Network loses plasticity

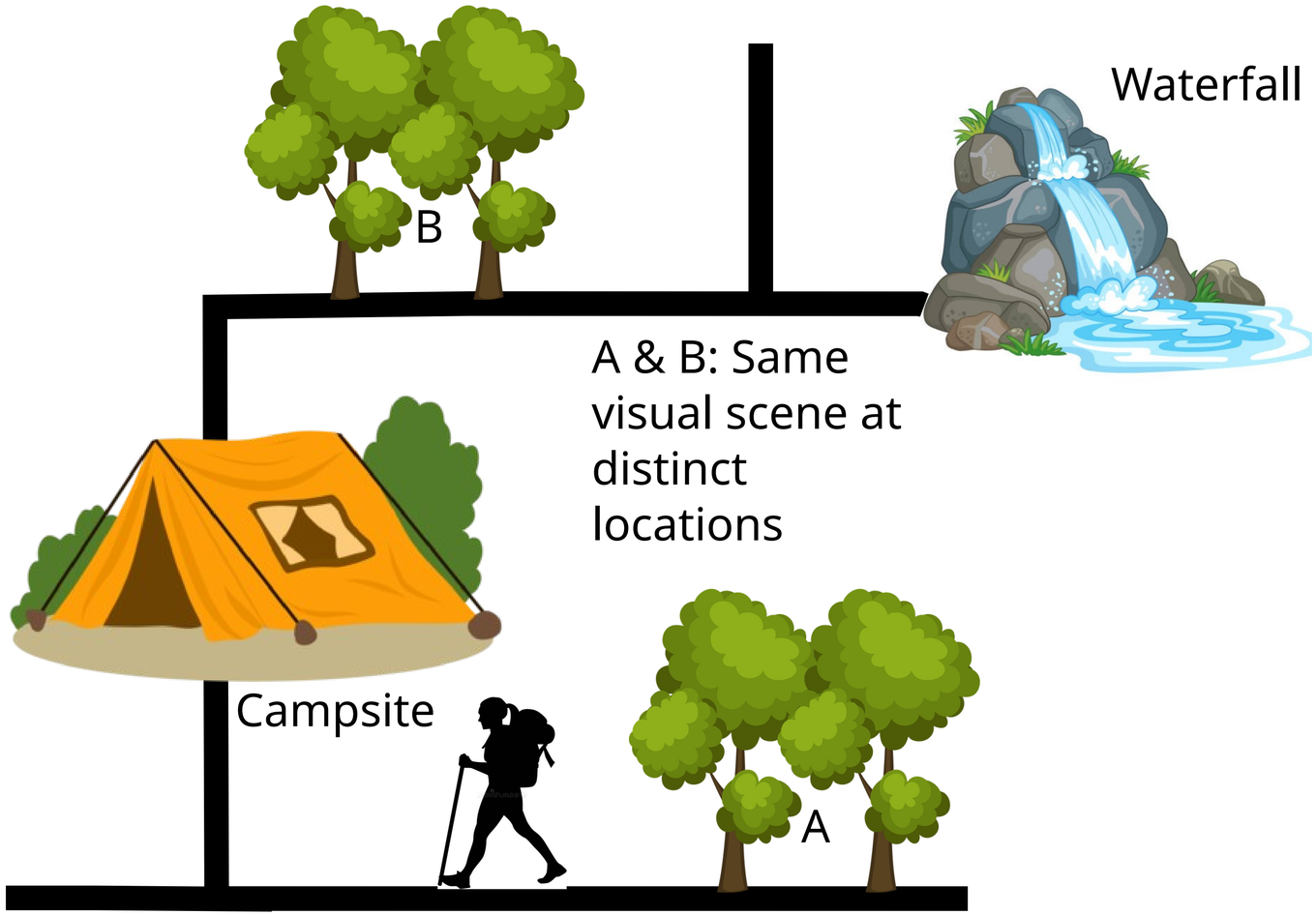


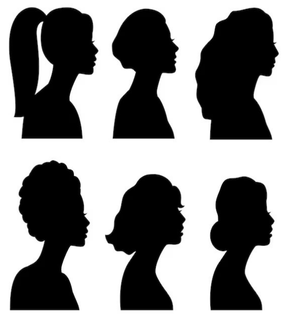
Neurons become dormant/ disengaged

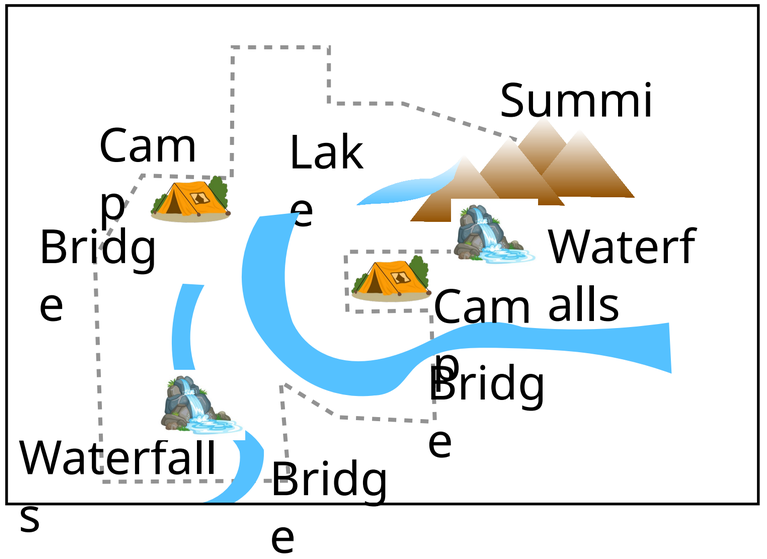
Memory maintenance

Learning

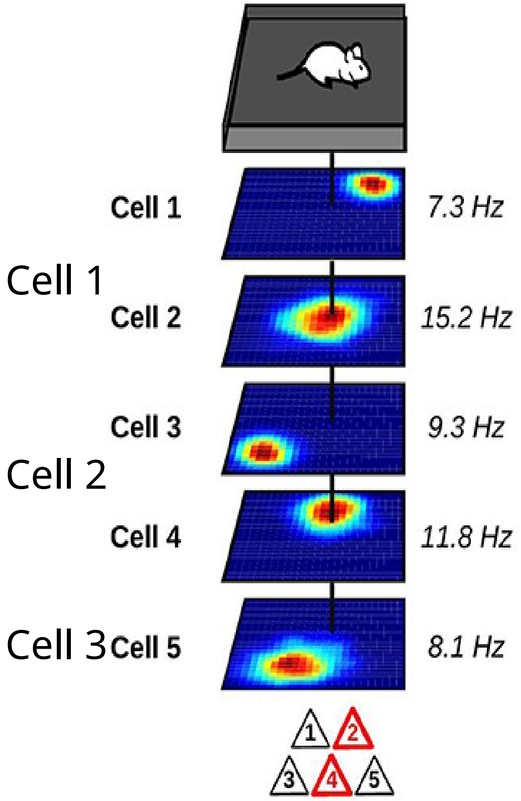
Sensory ambiguities and the need for cognitive maps



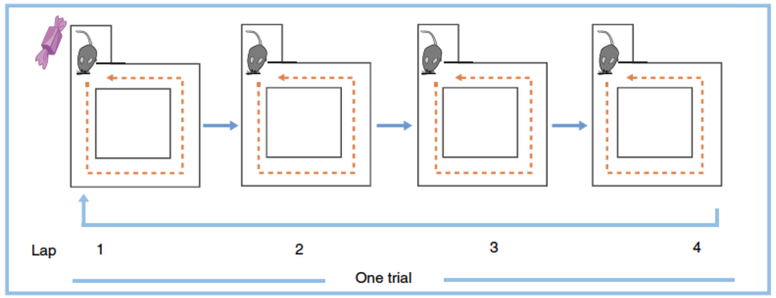




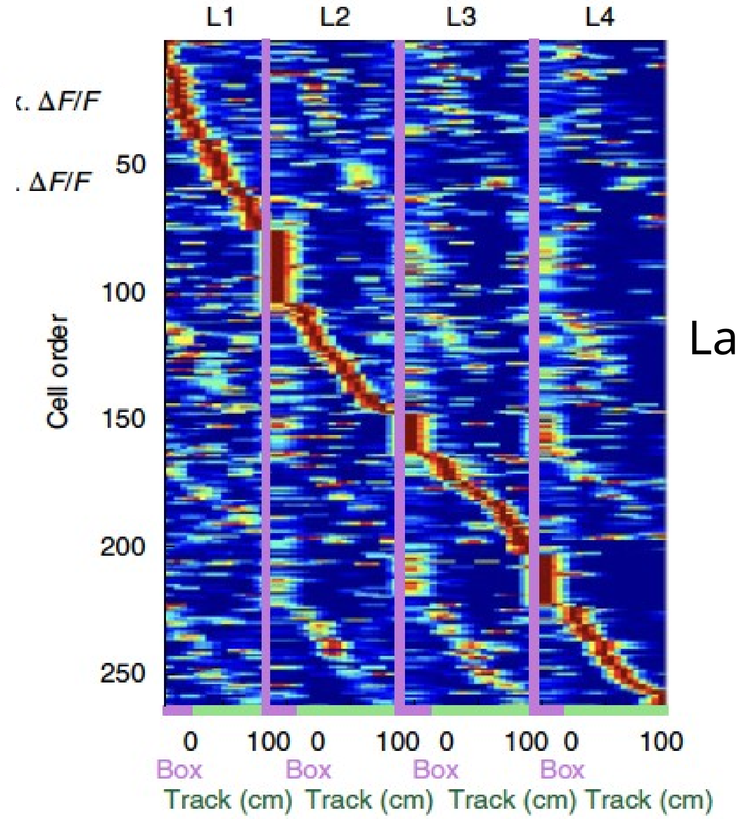
Looking in the brain: spatial and context/task dependent maps



Place Cells







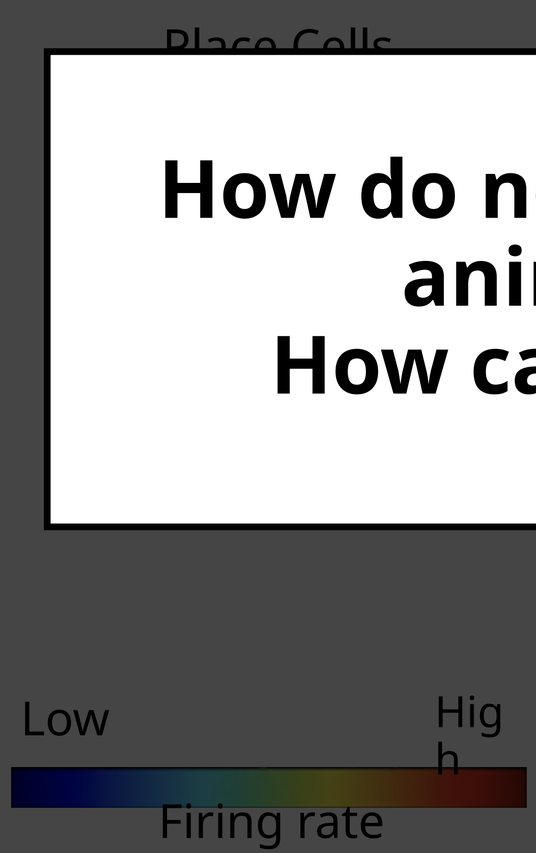
Lap Cells

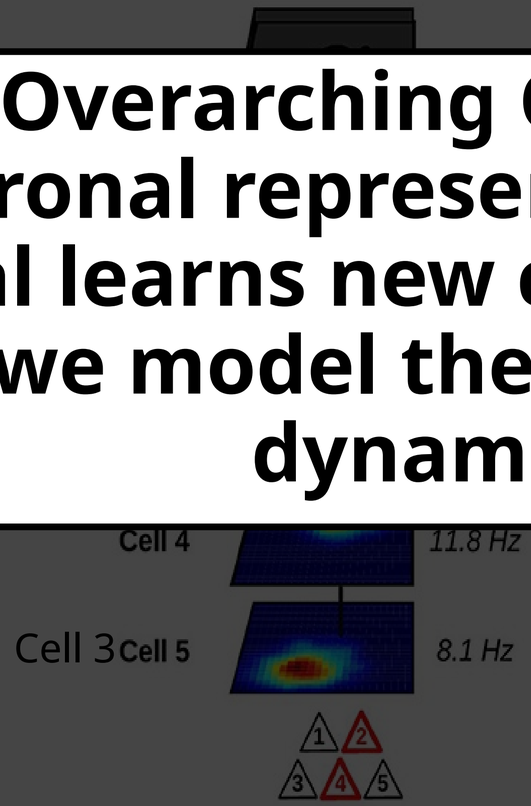
Sun et al., *Nat. Neurosci.*, 2020.

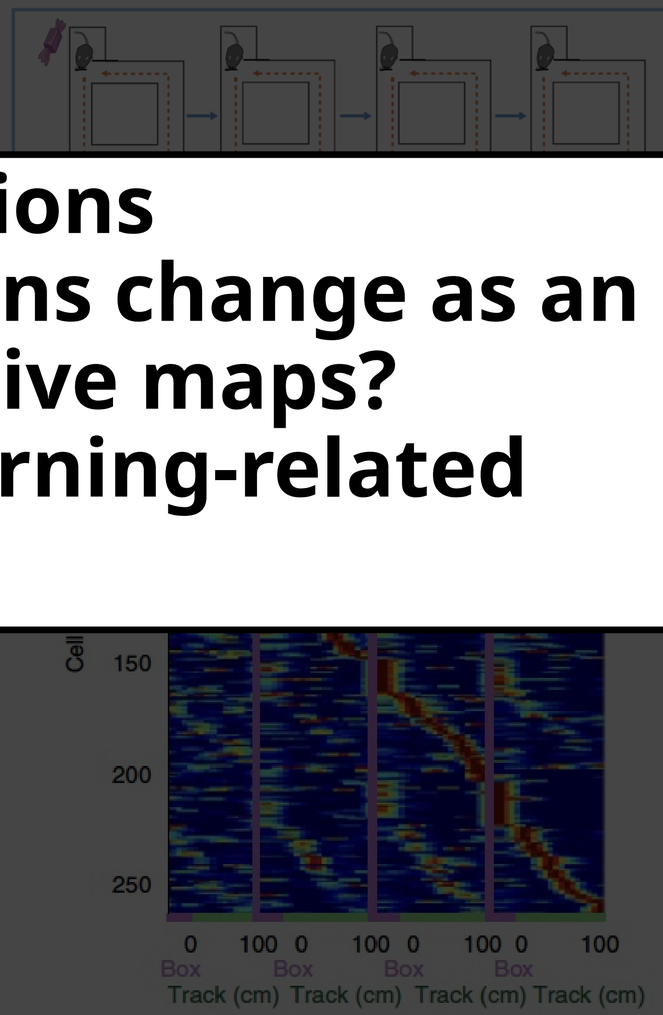
O'Keefe & Dostrovsky, *Brain Res.*, 1971.
Latuske et al., *Behav. Neurosci.,* 2018.

Looking in the brain: spatial and context/task dependent maps

Overarching Questions
How do neuronal representations change as an animal learns new cognitive maps?
How can we model these learning-related dynamics?





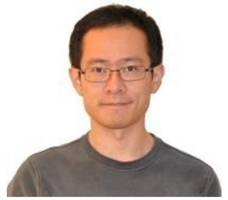


Sun et al., *Nat Neurosci*, 2020.

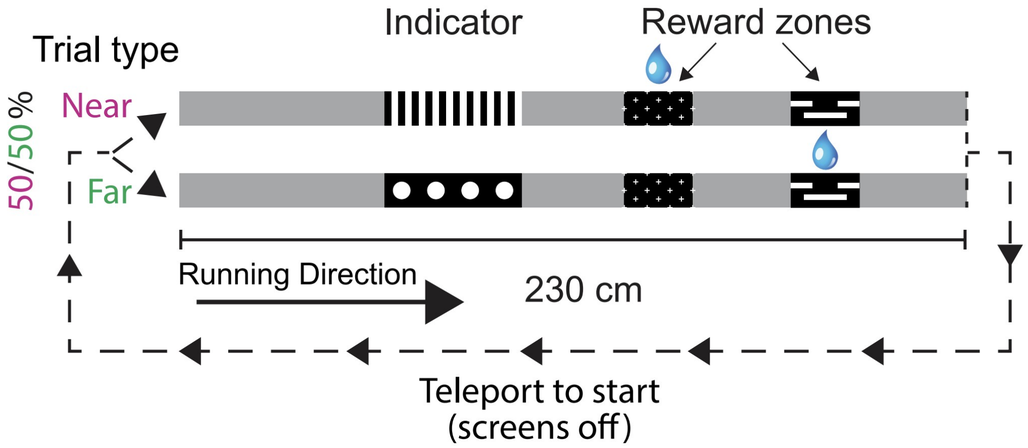

Nelson Spruston

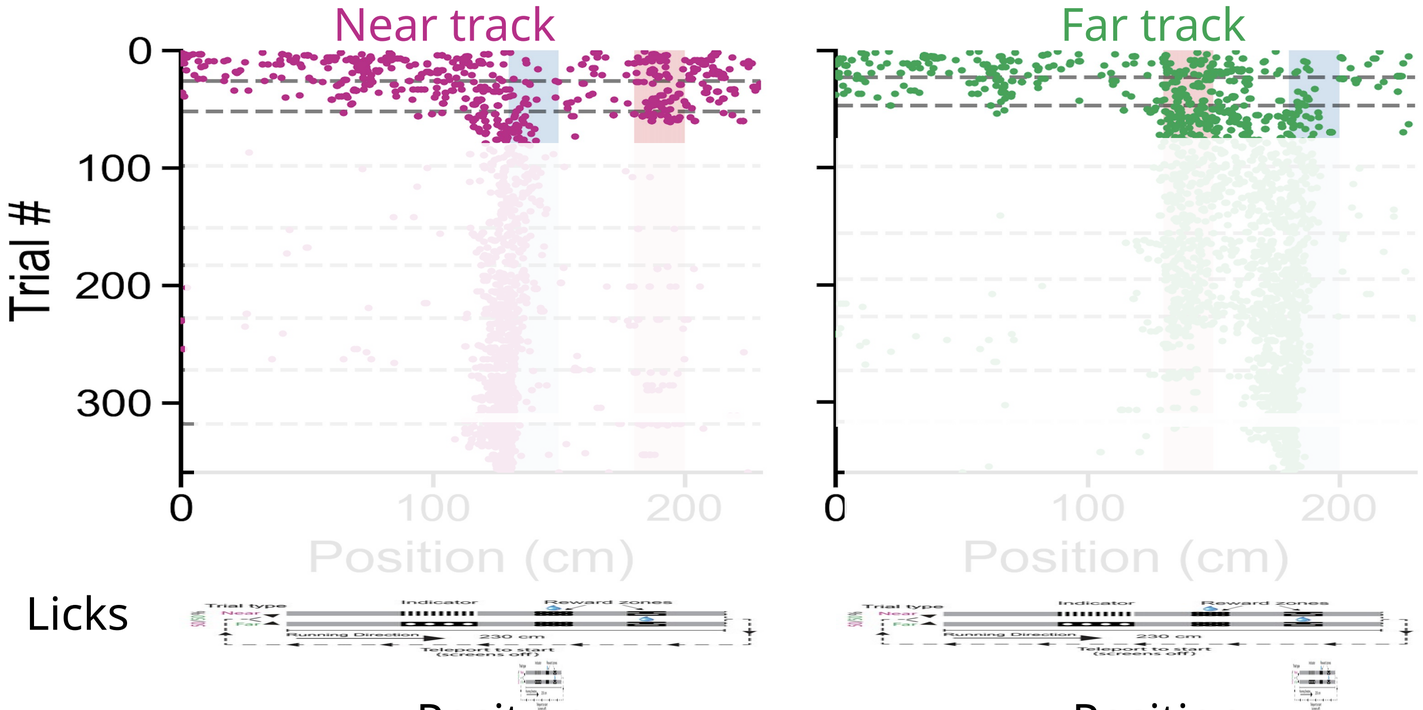

James Fitzgerald

Environment & behavior


Weinan Sun


Johan Winnubst





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Session separators

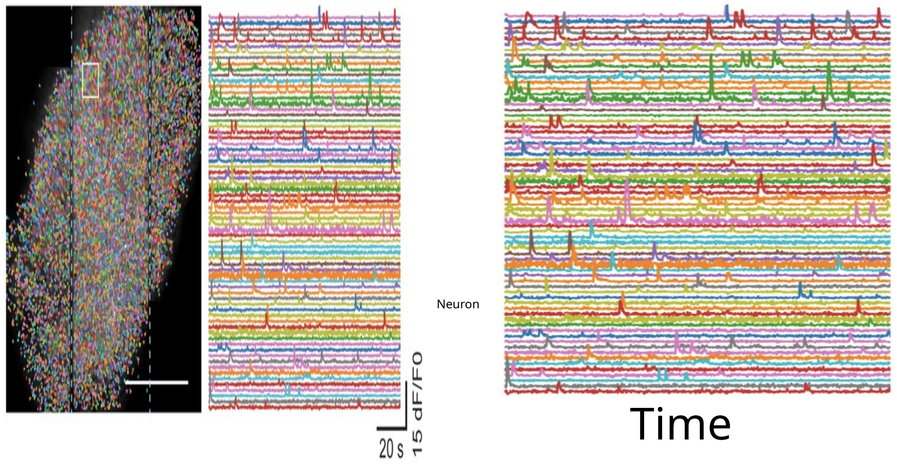
Licks

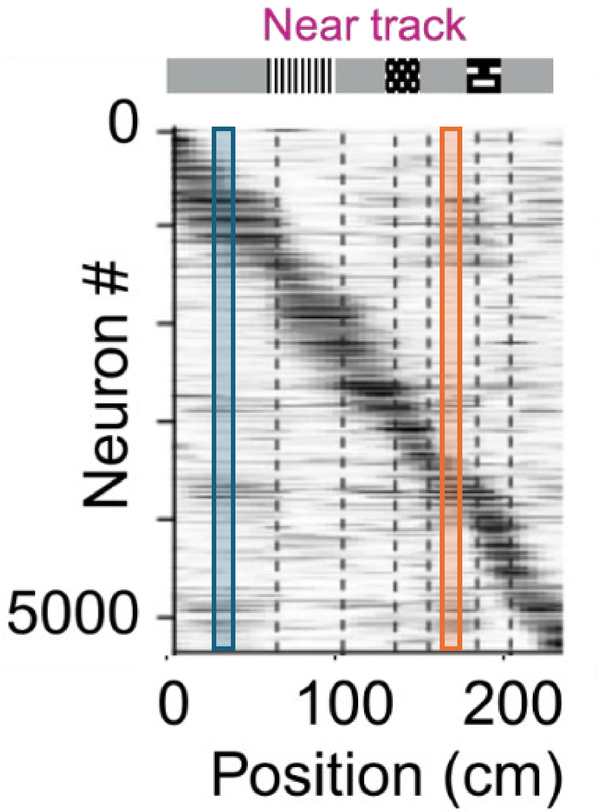


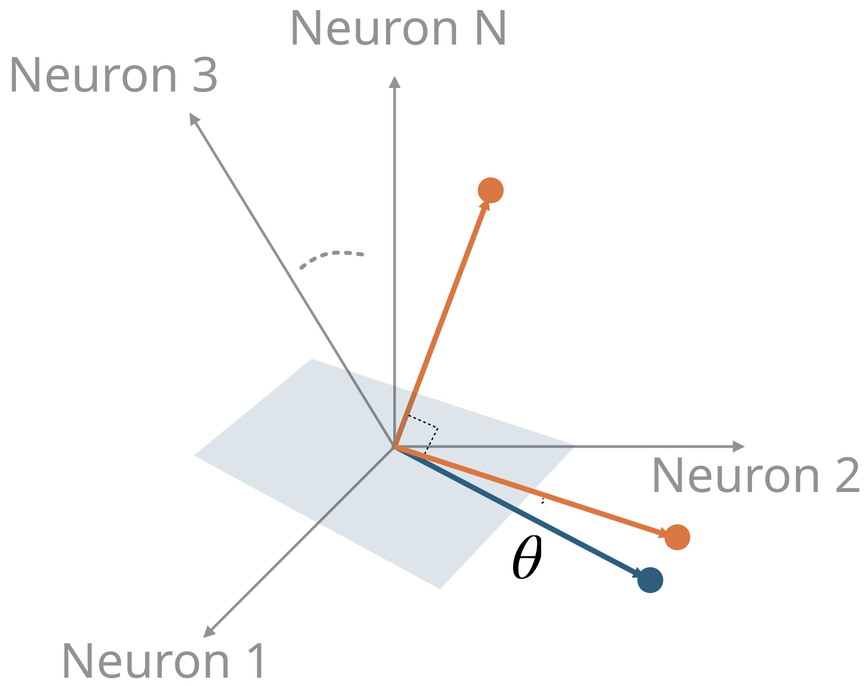
Rewarded location

Non-rewarded location

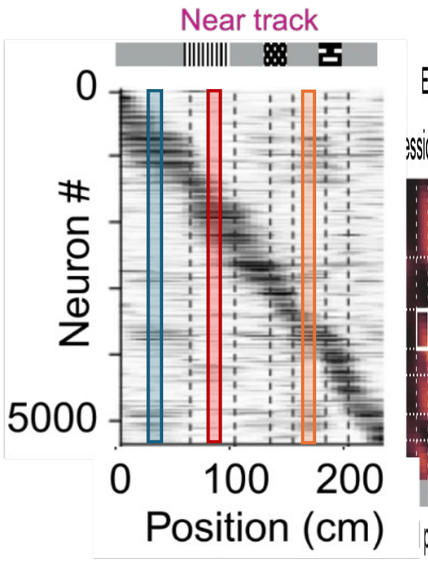
Neural response

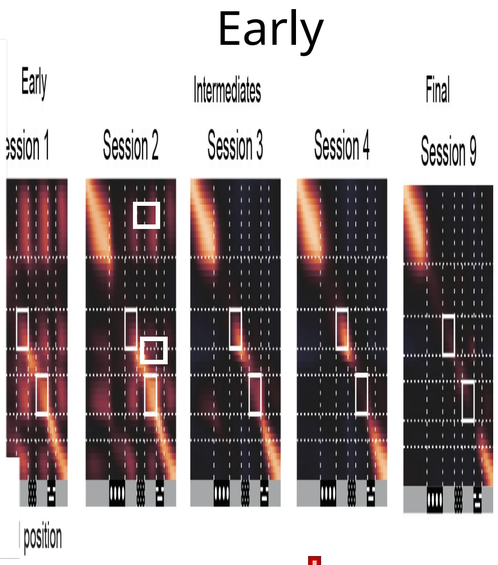


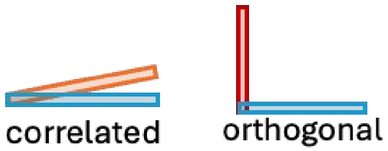


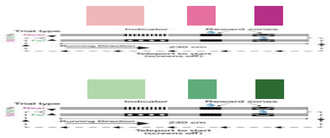


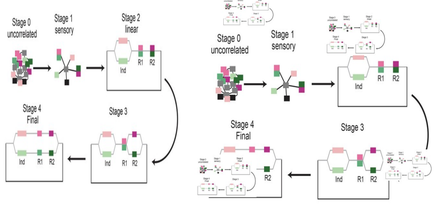
Decorrelation from sensory to orthogonal task state representation







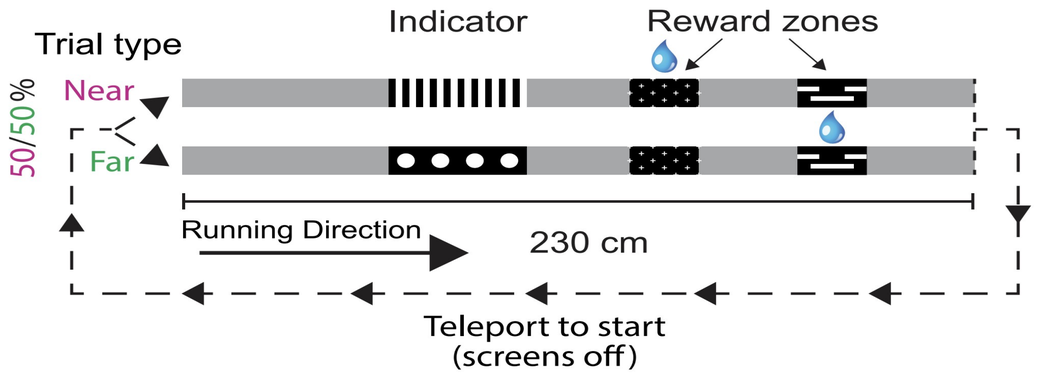






Time

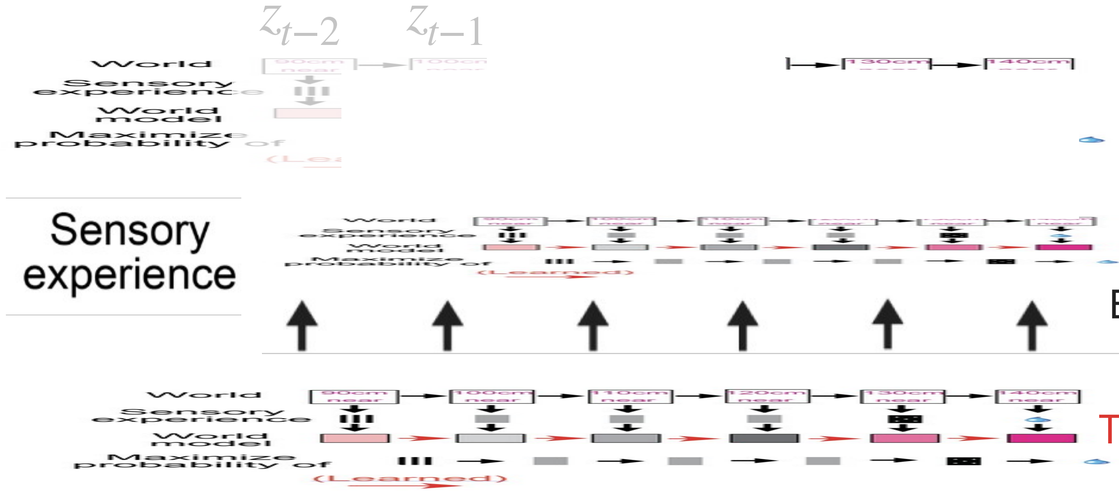
Hidden Markov Model (HMM): Learning world model from sensory sequences



Continuous experience into discrete observations



x_t



World into discrete states

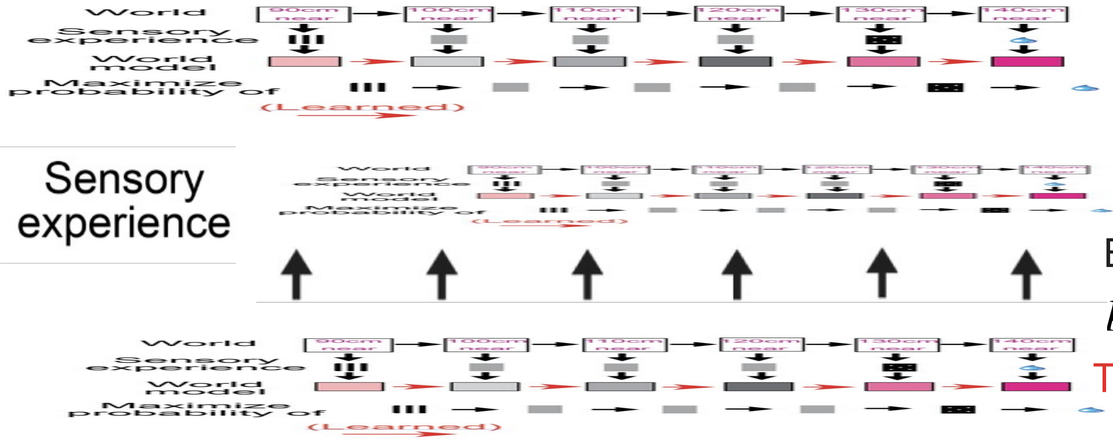
Emission probabilities $p(x_t \mid z_t)$

Transition probabilities $p(z_{t+1} \mid z_t)$

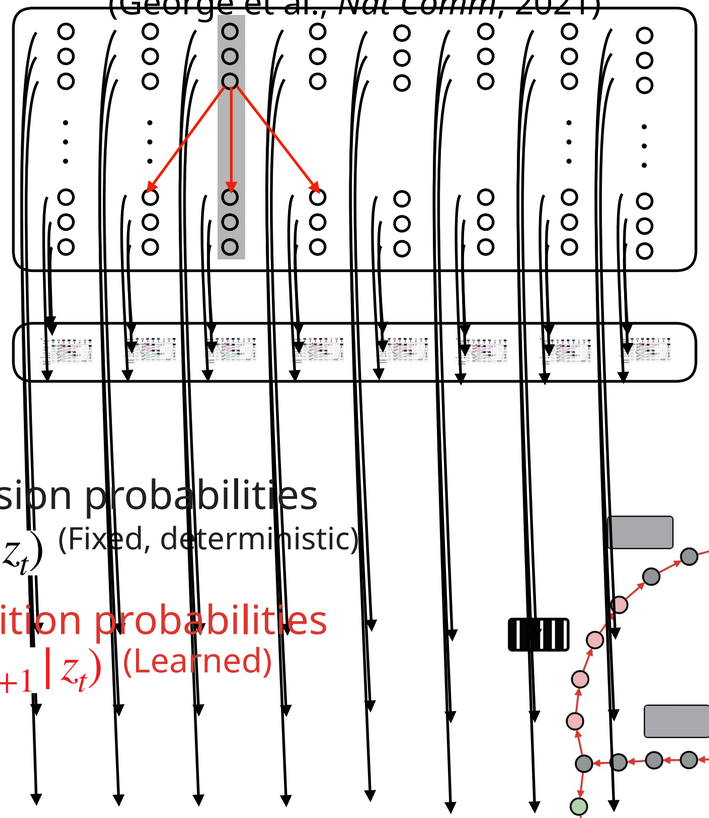
Goal: To build a world model or internal map

Learning transition probabilities to build a cognitive map

Goal: To build a world model or internal map



Clone-structured cognitive graph
(George et al., *Nat Comm*, 2021)

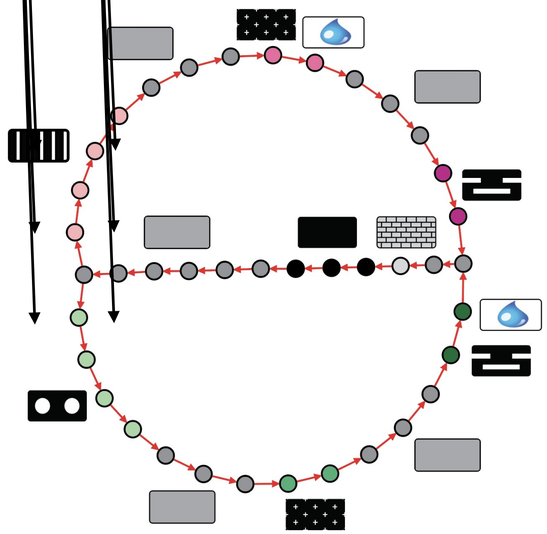


State/ Clone Probability

Neuron Firing rate

Emission probabilities
$p(x_t \mid z_t)$ (Fixed, deterministic)

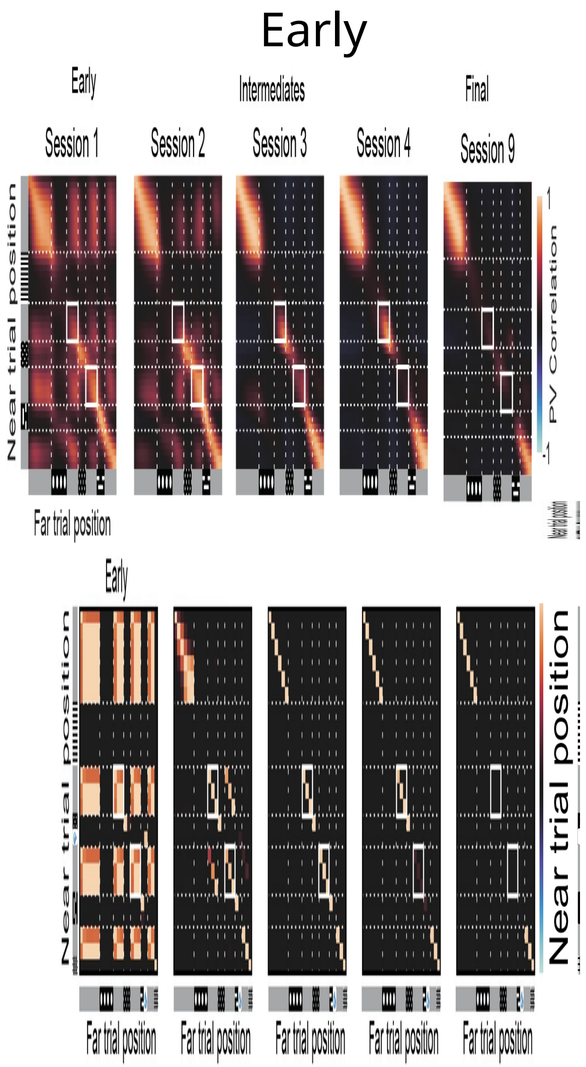
Transition probabilities
$p(z_{t+1} \mid z_t)$ (Learned)

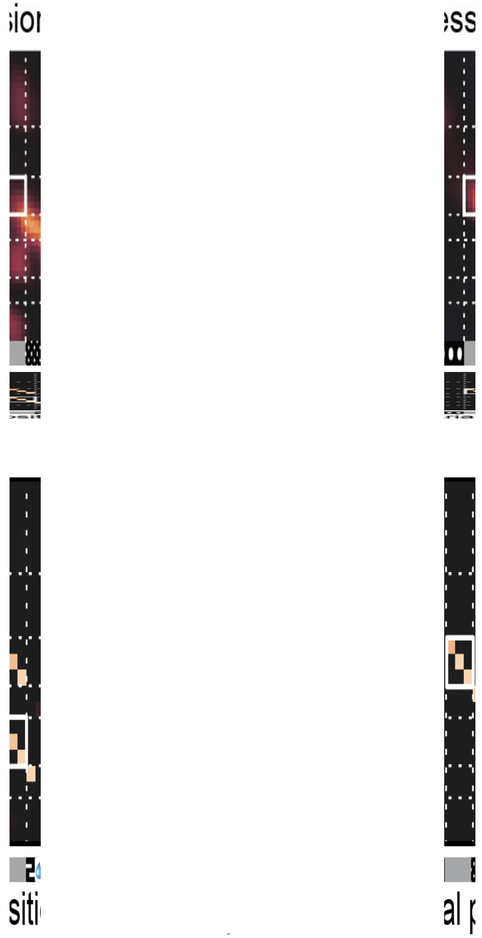


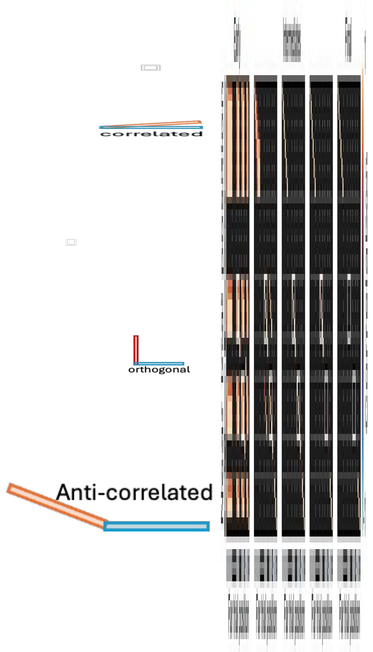
To maximize the probability of observed sensory sequence

$$p(x_1, x_2, x_3, \ldots x_T)$$

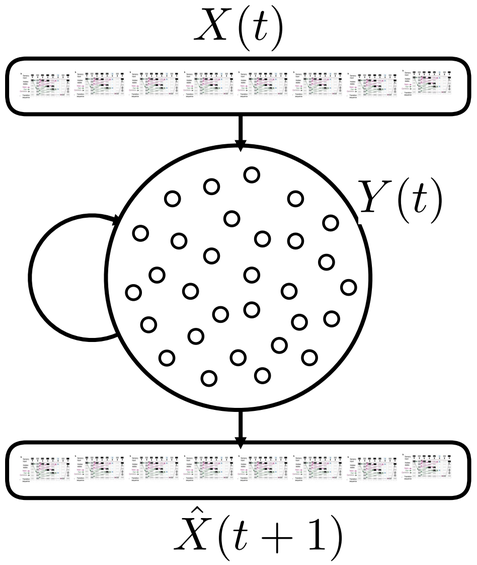
HMM learning captures the final orthogonal map and the learning process

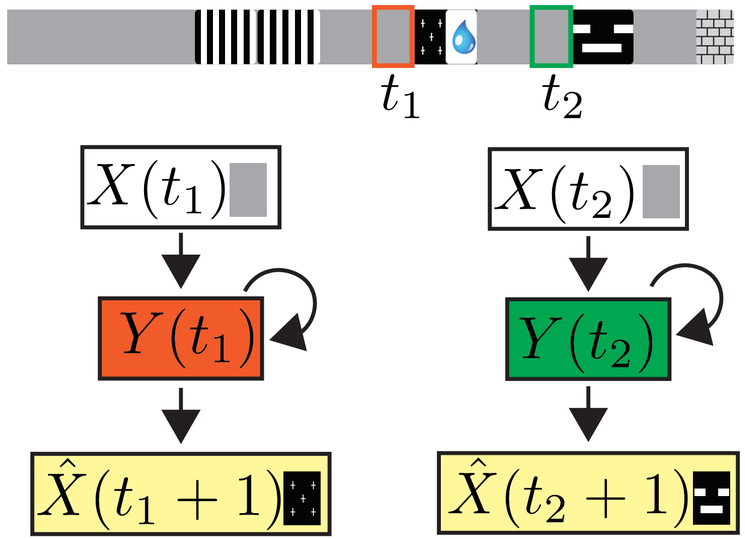


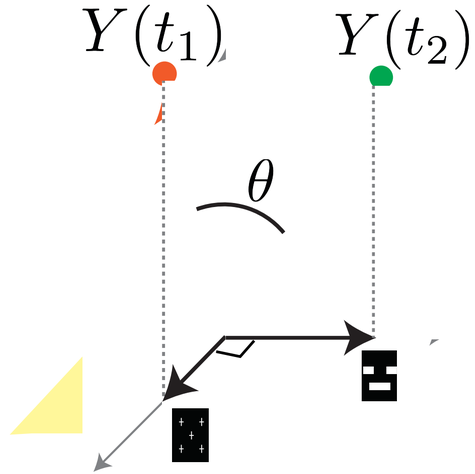




Orthogonalization is a non-trivial solution that confers robustness

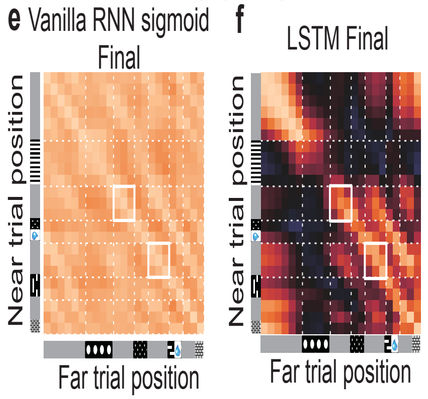




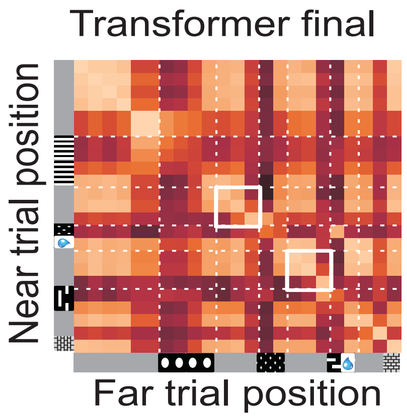


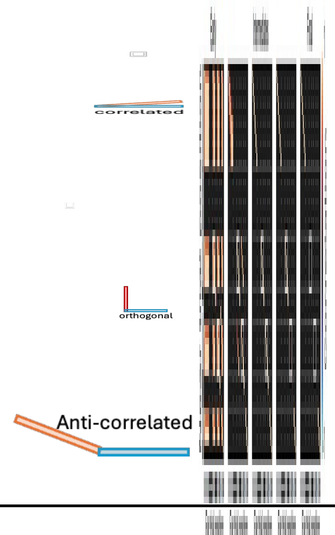
Machine Learning (ML) Models

Recurrent network



Transformer







+ Noise =

Confusion



+ Noise =

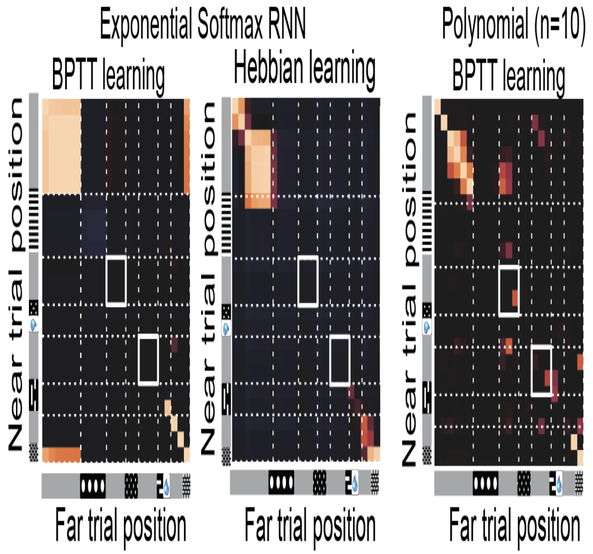


Can still distinguish

Matching the final orthogonalized map

Mimicking PMA with RNN

Final map



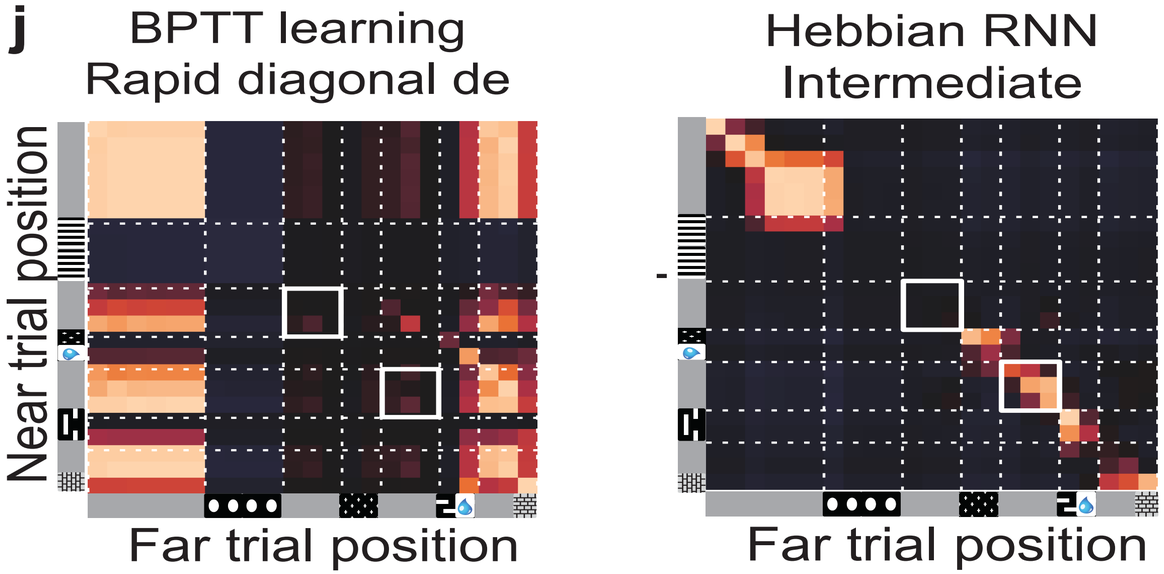
Helping ML models learn more robust maps

Matching the learning trajectory is highly non-trivial

Intermediate maps

Backpropagation

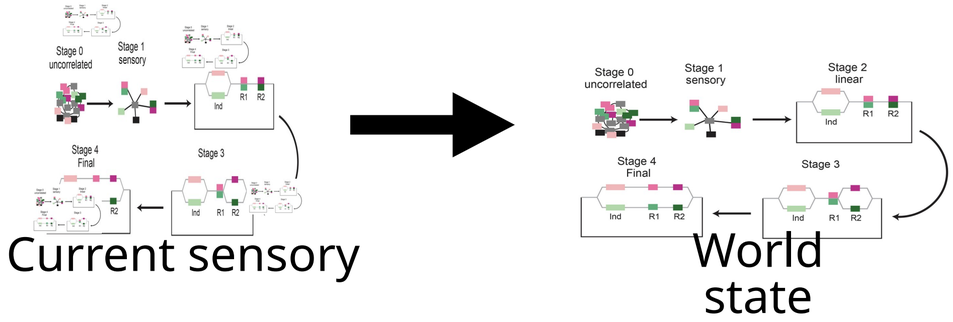
Hebbian Learning



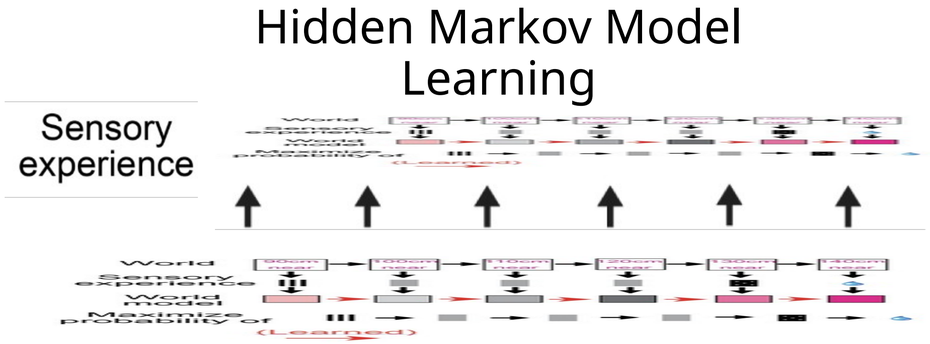
How do neuronal representations change as animals learn cognitive maps of new environments?

Mimicking an HMM with NN



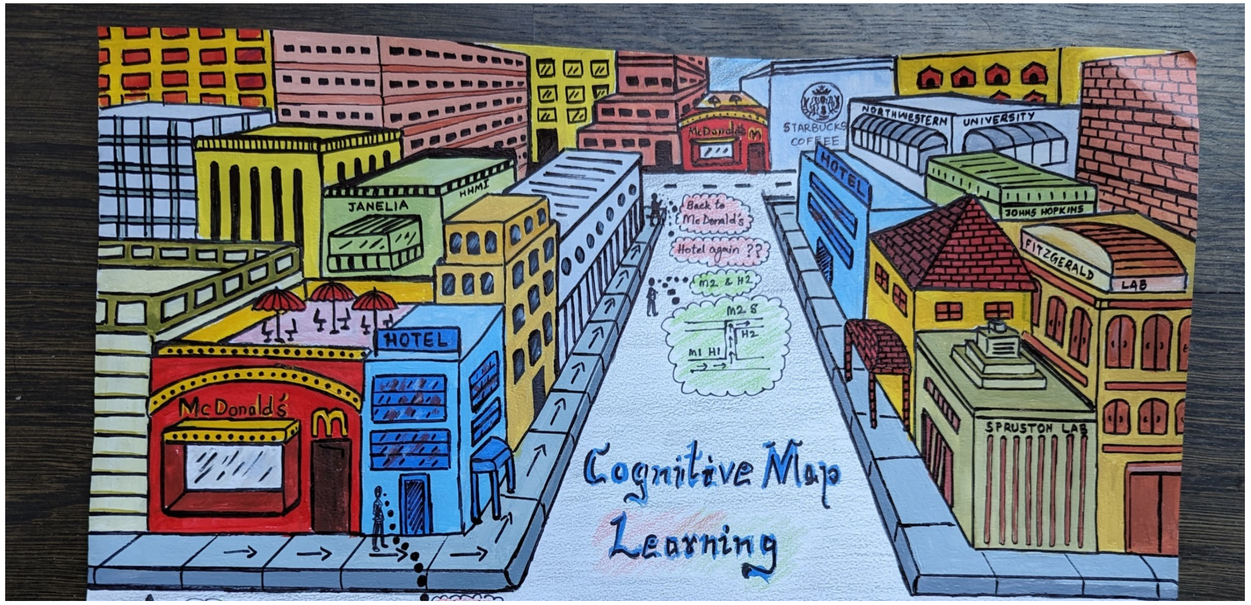


How can we model these learning dynamics?

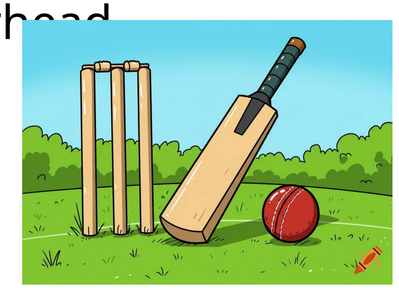


Sun, W., Winnubst, J., Natrajan, M. *et al.* Learning produces an orthogonalized state machine in the hippocampus. *Nature* (2025).

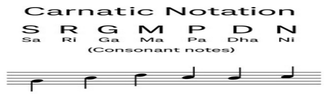
Cognitive Maps Beyond Space: Language, Music, and More



As a cricketer picked up his **bat**, a **bat** flew overhead







R	M	|	P	D	M	P	|	D	P	|	M	G	R	S	|
Ka	ru	|	na	Sa	ga	ra	|	ka	ri	|	va	da	-	na	|
S	R	|	M	-	G	R	|	S	R	|	G	R	S	,	|
Lam	-	|	bo	-	dha	ra	|	la	ku	|	mi	ka	ra	-	|
R	M	|	P	D	M	P	|	D	P	|	M	G	R	S	|
Am	-	|	ba	-	su	tha	|	a	ma	|	ra	vi	nu	tha	|

Stability through plasticity: Finding robust memories through representational drift

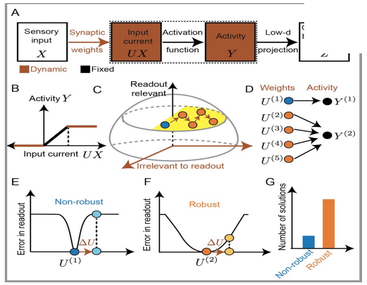
Natrajan, M., Fitzgerald, J.E., *PNAS, 2025*

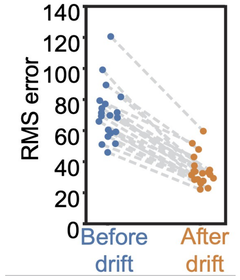
Robust regime
Sparsely engaged

Drift

Allocation

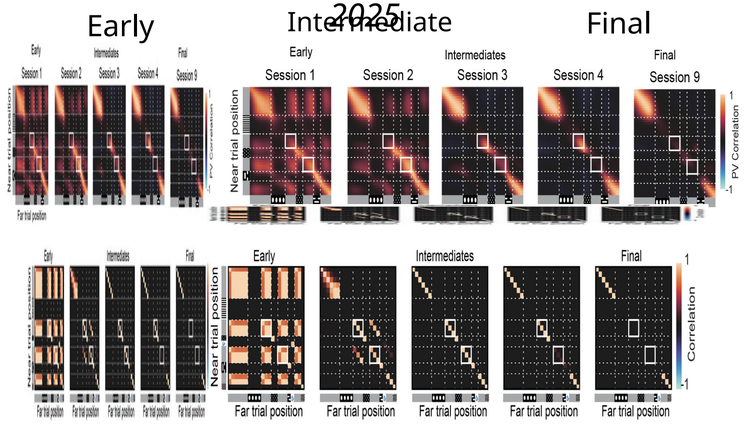
Learnable regime
Densely engaged





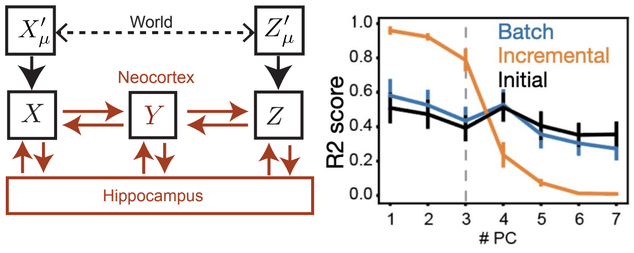
Learning produces an orthogonalized state machine in the hippocampus

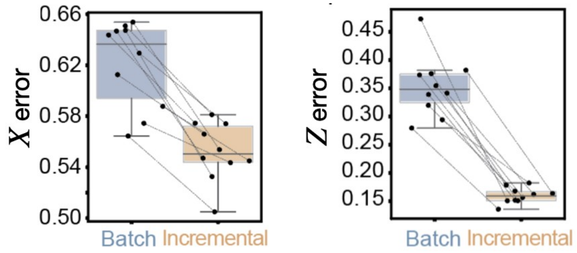
Sun, W., Winnubst, J., **Natrajan, M.** *et al., Nature, 2025*



Replay-Guided Local Rules Benefits from Incremental Experience

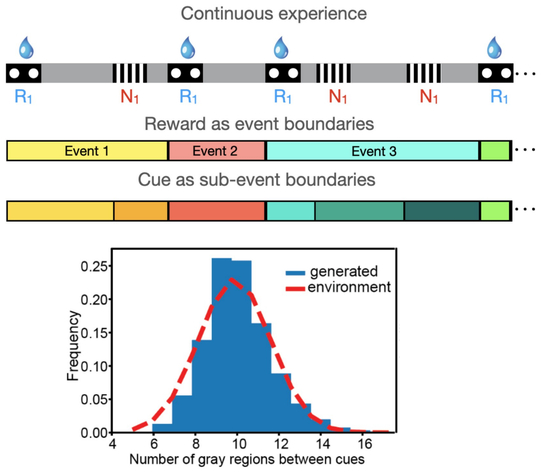
Natrajan, M., Saxe, A., Fitzgerald, J.E., *Manuscript in preparation.*





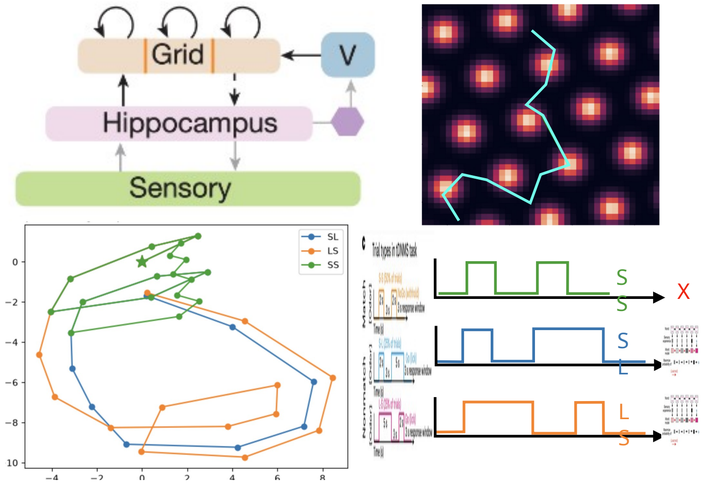
Hierarchical segmentation and probabilistic representation of continuous experience

In collaboration with Gabriela Michel, Kim Stachenfeld and others



Structure learning using a fixed grid architecture to flexibly encode space and time

In collaboration with Sarthak Chandra



Postdoc advisor



Sarthak Chandra

Collaborators



Weinan Sun



Johan Winnubst



Andrew Saxe



Gabriela Michel



Kim Stachenfeld



Andrew Fink

PhD Advisor & Lab



James Fitzgerald



Ryan Lu



Tirthabir Biswas



Benjamin James



Selim Chalyshkan



Ethan Baxter



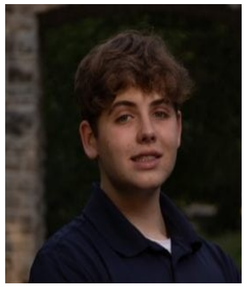
Santiago Guardo Maya



Dennis Wu



Corbin Diaz



Caden Holcomb



Yuqi Liu



Lina Morhai

Thesis committee



Nelson Spruston



Sandro Romani



Jim Knierim



Ann Hermundstad